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Balancing continuity of care and home care schedule costs using blueprint routes

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ABSTRACT

In a home care setting, high-quality care is typically associated with continuity of care. In addition, the increasing pressure due to labor shortages calls for cost-efficient operations. This paper focuses on obtaining cost-efficient daily schedules over a longer time horizon, with balanced shift lengths, while ensuring continuity of care (using the continuity of care index). To address this challenge, we propose a novel method based on blueprint routes. This method generates daily schedules by constructing optimized shifts and routes with regard to travel time, (time window) waiting time, and shift costs based on hourly wages. To ensure continuity of care, the daily scheduling decisions are strategically guided using the concept named blueprint routes. The blueprint routes are pre-optimized (partial) routes that help to align the daily schedules to achieve continuity of care in the subsequent nurse-to-shift assignment. Model-based evolutionary algorithms are employed to overcome the NP-hardness of the routing problem and nurse-to-shift assignment. Real-life-based numerical experiments demonstrate that continuity of care does not have to compromise home care schedule costs significantly.

1. Introduction

In recent years, like in many other Western countries, the service operations of Dutch home care providers have come under increasing pressure. On the demand side, there is a surge in the need for home care, mainly due to demographic aging and a shift from providing care in an inpatient setting to providing care (closer) at the client's home [1]. Meanwhile, there is growing pressure on the supply side, mainly caused by increasing labor shortages and high absenteeism rates [2]. Given this increasing pressure on their daily service operations, it is not surprising that a growing number of Operations Research (OR) studies try to optimize the home care schedules to utilize existing capacities maximally, see [3–6] for some recent overviews.

A prominent and topical issue in home care scheduling concerns continuity of care. In the clinical literature, it is widely believed that continuity of care is essential for providing high-quality care; see, for example, the systematic reviews [7,8]. In the home care context, continuity of care means that clients receive the required care from a limited number of nurses. Ensuring continuity of care leads to stability and therapeutic benefits of the relationship between the nurse and client (see, e.g., [9,10]), resulting in better health outcomes, functional improvement/stabilization, and fewer depressive symptoms [11]. Moreover, in [11] provider continuity is conceptualized as an indicator of close social relations between home care workers and their clients. From the nurse's perspective, this undoubtedly contributes to a positive work experience whereas continuity of care also provides structure and regularity.

Continuity of care is typically measured in OR literature by simply counting the number of unique nurses visiting a client (see, e.g., [12]), which unfortunately falls short in practice. In particular, this measure does not scale with the frequency of visits per client, as we will show in Section 3.2, and leads to ambiguity in the valuation of different nurse configurations; an illustrative example of the ambiguity of the number of unique nurses as a measure of continuity can be found in Figure 1 of [13]. Our study assesses continuity of care in relation to home care scheduling, using the Continuity of Care Index (CCI), as defined in, e.g., [7,14] and used in, e.g., [11]. The CCI is designed to mitigate potential issues associated with other measurement methods. It incorporates factors such as the frequency of visits, the range of nurses involved, and the care coordination among nurses. A higher CCI-score indicates a more consistent and coordinated experience. As mentioned, continuity of care is a crucial metric for providing high-quality care. However, next to continuity of care, care must also be delivered at the desired moment without inducing clients' waiting time and nurses' overtime. Moreover, next to the clients, the service providers and operators are the two other primary stakeholders [15]. Hence, in view of efficiency, travel time and operational costs (e.g., hourly wages) need

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to be minimized as well, whereas balanced shift durations are crucial requirements.

This paper focuses on obtaining cost-efficient home care schedules, with balanced shift lengths, combined with continuity of care (i.e., achieving a high CCI-score) in realistic instances. Given a set of (home care) jobs spread over a week, the goal is to (i) create shifts that specify the daily sequence of jobs to visit (typically referred to as *routing*) and (ii) assign nurses to the shifts (referred to as *nurse-to-shift assignment* or *rostering*). Our aim is to establish a complete *schedule*. In view of (i) and (ii), this entails specifying the nurses assigned to each shift and detailing the clients served during those shifts along with the corresponding order. While routing primarily deals with managing operational costs, nurse-to-shift assignment is crucial regarding continuity of care. More specifically, the combined structure of the daily schedules over the entire horizon must facilitate continuity of care in the nurse-to-shift assignment. Hence, an integrated scheduling approach is required to balance continuity of care and schedule costs. The schedule costs in our work are defined in terms of travel time, (time window) waiting time, shift overtime, and hourly wages. It is worth noting that in the literature, the term 'schedule' varies in interpretation across studies; for example, some studies also allocate jobs to days as part of the scheduling instead of taking it as input.

In the nurse-to-shift assignment of (ii), it is customary in the OR literature to consider a predetermined set of nurses, each contributing specific constraints based on their preferences and availability. In this framework, it is necessary that the shift design of (i) is compatible with those constraints. However, in this paper, we diverge from the conventional OR approach by composing a set of nurses that fits the shift design, rather than using a predetermined set of nurses. This approach is inspired by the repeated question from our partner home care organization concerning the ideal composition of a nursing home team. The goal of our nurse rostering component is to provide a planning where the nurses act as placeholders. This is motivated by the fact that the final rostering of nurses differs significantly between organizations and is a delicate process, typically involving various manual steps and tacit knowledge [16]; e.g., in [17] self-rostering has been reported as the most common rostering style in hospitals. Nevertheless, our nurse rostering component ensures that the shift lengths are compatible with typical nursing contracts, i.e., conform to workforce rules and regulations, and represent a fair schedule from the perspective of nurses.

The considered home care scheduling problem is challenging because (i) both the routing and rostering are NP-hard problems on their own, (ii) the routing and rostering are interdependent, and (iii) a larger time horizon must be considered to address continuity of care. Consequently, solving the scheduling problem using standard (meta-)heuristics is infeasible for realistically sized instances.

To solve our home care scheduling problem in real-life settings, we develop a framework to dissect the complete scheduling problem into coherent daily scheduling problems using so-called *blueprint routes*. The blueprint routes, that are pre-optimized upfront, comprise sets of (partial) efficient routes via jobs with frequent occurrences throughout the time horizon. These blueprint routes are designed to serve as guiding structures during the daily scheduling optimization, laying the foundation to facilitate continuity of care in the nurse assignment over the complete time horizon. The sub-problems of blueprint route determination, daily scheduling, and nurse assignment are all solved using (model-based) evolutionary algorithms to combat NP-hardness.

In conclusion, our contribution is three-fold:

1. We introduce a home care scheduling problem in which a broad spectrum of practically relevant costs are considered while taking continuity of care into account as measured by CCI, a measure which has not been utilized in the home care scheduling literature before. We show that CCI scales well with the number of visits, which does not hold for the unique number of nurses. A key feature is that the shifts are not predefined, such that the optimal shift composition can be determined, which is crucial for tactical home care planning.
2. To connect daily scheduling with continuity of care, which operates on a longer timescale, we use a new concept of blueprint routes. Based on this concept, an algorithm is developed that can efficiently solve realistic home care scheduling problem instances. While both home healthcare routing and scheduling as well nurse rostering have been intensively studied in the literature, a main methodological contribution of this paper lies in how we soundly connect and combine them using those blueprint routes.
3. Numerical experiments based on Dutch home care data demonstrate that continuity of care does not have to compromise schedule costs much, which gives hope that high-quality home care can also be provided in the future despite societal challenges.

This paper is organized as follows. In Section 2, we discuss the related literature. Section 3 introduces the home care scheduling model, provides background concerning the CCI, and presents the objective formulation. Section 4 introduces our solution method based on blueprint routes. In Section 5, we compare the solution method with several benchmarks using real-life inspired numerical experiments. Section 6 concludes our study.

2. Related literature

There exists a large body of literature with respect to the two separate research areas of routing and rostering; we first briefly address the routing literature in Section 2.1, followed by rostering literature in Section 2.2.

2.1. Routing

In the home care context, the routing problem is typically referred to as the Home Health Care Routing and Scheduling Problem (HHCRSP), we refer to [3–5] for some recent literature reviews. In the HHCRSP, various objectives are considered for the quality of the routes; a detailed overview is provided in [4]. In line with the literature, our focus is on travel time, overtime, and (time window) waiting time, related to the goals of the service provider, nurses, and clients, respectively. Moreover, we also consider optimized shift lengths based on hourly wages of different nurse types. To the best of our knowledge, such a tactical decision is not incorporated in the HHCRSP literature.

The number of studies that consider schedule costs in conjunction with continuity of care is limited. In [18], the authors consider the trade-off between travel time and continuity of care in the context of midwives visiting clients. In [12], next to travel time and continuity of care, the authors include overtime and the number of unscheduled jobs in the objective. Moreover, [12] introduces the master schedule problem, which involves constructing a basic schedule that can be repeatedly applied from week to week (irrespective of the nurses). While the underlying idea of the master schedule problem shares similarities with our concept of blueprint routes, there is a clear difference in objectives. Specifically, the focus of the master schedule problem in [12] is on minimizing the number of routes, whereas our approach aims to identify 'strong' combinations of activities, in order to reduce schedule costs and facilitating continuity of care. In [19], the authors address the HHCRSP by formulating it as a set partitioning problem. Their aim is to assign predetermined routes to nurses in a way that minimizes various costs associated to the routes, weekly nurse overtime and idle time, and the number of unscheduled visits. The costs associated to the routes include travel time, continuity of care scores, shift length violations, and the number of unmet client preferences. To solve the set partitioning problem, the authors employ a large neighborhood search method to generate potential routes, which are then assigned to nurses using a constructive set partitioning heuristic. However, unlike our approach, their method does not specifically generate routes to facilitate continuity of care. In [20] the HHCRSP is solved using a branch-and-price algorithm. This algorithm is divided into two main components: a pricing problem that generates daily schedules for individual nurses and a master problem that combines these daily schedules into a feasible overall solution. The objective of their model consists of travel time, nurse busyness, and quality of service, which includes continuity of care. The authors in [13] combine travel time with continuity of care and preference costs between nurses and clients.

In other studies, continuity of care is incorporated as a constraint rather than an objective. The authors in [21] consider the trade-off between costs in hourly wages and patient satisfaction (measured in additional service time) under continuity of care constraints. Similarly, [22] focus on minimizing travel time and CO2 emissions while ensuring continuity of care through the constraints of their model. Notably, continuity of care is sometimes indirectly achieved by optimizing the preference association between clients and nurses jointly with minimizing travel time. For example, [23,24] focus on optimizing client-nurse preferences as part of their objective, thereby indirectly including continuity of care.

In all OR-related papers continuity of care is measured based on counting the number of different nurses. We are the first to employ CCI as a more comprehensive measure for continuity of care in a home care scheduling context. Moreover, our work distinguishes itself by using a more comprehensive scheduling objective that includes overtime and (time window) waiting time, along with travel time. Additionally, we create optimized shifts that allow for tactical home care planning.

Finally, some studies explore continuity of care within related HHCRSP settings. For example, [25,26] incorporate continuity of care together with other performance measures in the HHCRSP under stochastic parameters, such as travel time and service time. Additionally, [27,28] address continuity of care under dynamic conditions, including changes in the client pool and the availability of nurses.

2.2. Rostering

In the rostering literature, there are two common approaches for assigning nurses to jobs. The first approach is to assign the nurses directly to the jobs (see, e.g., [29]). Alternatively, nurses can be indirectly assigned by placing them on shifts containing a predetermined job set (see, e.g., [12]). The second approach, which relates to our approach, can be considered as a variant of the well-known Nurse Rostering Problem (see [30,31]). When it comes to the nurse assignment, continuity of care is often studied together with the workload balance of the nurses. In many of these studies, the main focus is to optimize the workload balance, while continuity of care is of secondary importance by including it as a constraint (e.g., by limiting the number of unique nurses that visit a client), see for example [32–34]. Nonetheless, sometimes both are included in the objective of the model, as in [35]. Finally, there are also studies focusing on the nurse-to-patient assignment, with a central focus on continuity of care [15,36,37]. In those papers, next to continuity of care, workload balance is also paramount. In contrast to our work, the efficiency of the route is not explicitly considered.

In terms of rostering, our approach parallels that of [38], where we primarily focus on continuity of care rather than an even distribution of workload among nurses. Albeit we do not specifically balance the workload, our shift design and penalty for overtime implicitly allow for a balanced workload distribution. Moreover, we do adhere to certain general constraints according to the workforce rules and regulations of the nurses. While [35,38] primarily focus on rostering, with limited attention to routing, we are tackling a more comprehensive routing problem.

3. Problem description

In this section, we introduce the model to address our planning problem in the home care setting. This involves scheduling various care activities to shifts and assigning nurses to those shifts. The full model is introduced in Section 3.1, Section 3.2 provides insight into the CCI, and the model's objective to evaluate the quality of the planning is formalized in Section 3.3.

3.1. Home care scheduling model

The premise of the model is a set T of consecutive days up to a given horizon. For example, a horizon of 7 days represents one week, with $T = \{1, 2, \ldots, 7\}$. On each day $t \in T$, a set of geographically dispersed jobs J_t is provided, where a job $j \in \cup_{t\in T} J_t$ belongs to a client $k \in K$, with K the set of all clients. It is possible that multiple jobs belong to the same client, as a client may have different types of care activities going on at the same time (examples are assistance with personal hygiene, meal preparation, medication management, and wound care). Furthermore, note that the same job may appear on multiple days, i.e., for $t_1, t_2 \in T$ with $t_1 \neq t_2$, it may hold that $J_{t_1} \cap J_{t_2} \neq \emptyset$; this represents that care activities are repeated over the time horizon (e.g., daily assistance with preparing meals). In Fig. 1, an illustrative example is given of a set of jobs with corresponding clients over a horizon of one week.

In the subsequent paragraphs, we will provide precise definitions of the key components involved in the model, i.e., 'jobs', 'schedules', and 'planning', respectively.

Jobs. Each job j needs to be carried out by a nurse, where we have to take the service time, the time window, and the required qualification level of the jobs into account. The service time of job j is denoted by $p_j > 0$ and indicates the time it takes for the nurse to handle the job (it is assumed that the duration is independent of the specific nurse). The time window indicates when the service should start and consists of a start time and due time $0 \leq b_j^{(\mathrm{tw})} \leq e_j^{(\mathrm{tw})}$, respectively. It is not allowed for a nurse to start earlier than the time window start time $b_j^{(\mathrm{tw})}$, however, it is allowed to start later than the time window due time $e_j^{(\mathrm{tw})}$, which results in waiting time for the job (the exact definition of waiting time will be given in the next paragraph). The required qualification level of a job is denoted by $q_j^{(\mathrm{job})} \in Q$, where Q is the set of qualification levels and indicates whether or not a nurse may handle the job. To be more specific, if the qualification level of the nurse does not match the required qualification level of the job, the nurse is not allowed to handle the job. We impose an ordering on Q such that a nurse with (provided) qualification level $q^{(\mathrm{nurse})} \in Q$ is allowed to handle all jobs with a required qualification level $q_j^{(\mathrm{job})} \leq q^{(\mathrm{nurse})}$.

Schedules. For each day $t \in T$, a set of shifts S_t needs to be created, which is referred to as a schedule. Each shift $s \in S_t$ contains an ordered (non-empty) subset of jobs from J_t representing a route. Here, the jobs on the route are ordered by their planned arrival times $a_j \geq 0$, i.e., the time at which the nurse should arrive on site and start service. Clearly, the arrival times should respect the necessary time delay (i.e., service time and travel time) between subsequent pairs of jobs. To this end, define the variable $r_{sij} = 1$ if job i is handled right before job j on shift s, and $r_{sij} = 0$ otherwise. Additionally, we denote $d_{ij} \geq 0$ as the travel time between jobs i and j, and $w_j = \max(a_j - e_j^{(\mathrm{tw})}, 0)$ as the waiting time of job j. Now, whenever job i precedes job j on the route of a shift, the arrival time of job j should satisfy $a_j \geq \max\{a_i, b_i^{(\mathrm{tw})}\} + p_i + d_{ij}$. Together, all shifts on S_t should cover all jobs J_t, such that for each job $j \in J_t$, there is exactly one shift $s \in S_t$ that contains job j. A shift s has a start and end time denoted with $0 \leq b_s^{(\mathrm{shift})} \leq e_s^{(\mathrm{shift})}$, respectively. The start time of a shift is defined as the moment when the service of the first job (on the corresponding route) starts, and the end time of a shift is defined as the moment when the service of the last job is completed.

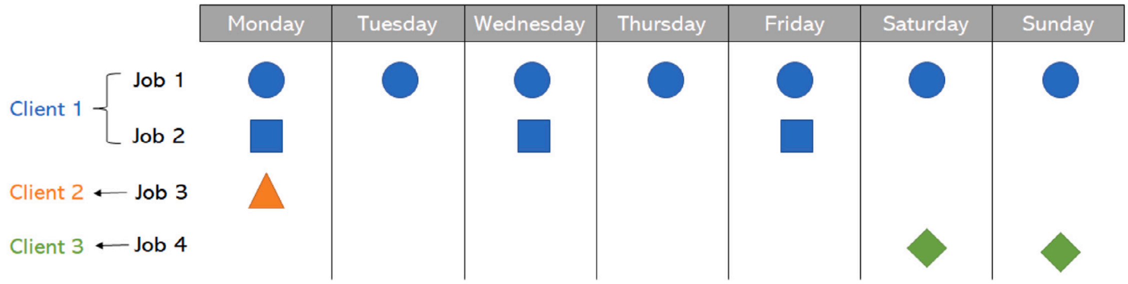


Fig. 1. Example of job set with corresponding clients over a horizon of one week.

The total duration of a shift s is defined as $u_s := e_s^{(\text{shift})} - b_s^{(\text{shift})}$. Note that a shift is thus completely determined by the properties of the corresponding route. However, we will view a route only as a subset of jobs ordered by their respective arrival times, whereas a shift refers to all additional features. Finally, we remark that a shift can also be viewed as a placeholder for a nurse.

Planning. Given a set of schedules over the full horizon $S := \{S_t | t \in T\}$ we want to assign nurses to the shifts in S in such a way that each shift $s \in \cup_{t\in T} S_t$ has exactly one nurse assigned to the shift. However, a nurse is allowed to be assigned to multiple shifts. To this end, we distinguish between a set of schedules before and after a nurse-to-shift assignment. That is, before a nurse-to-shift assignment the set of schedules is referred to as a *conceptual planning*, whereas we refer to the set of schedules as a *complete planning* once the nurse-to-shift assignment is completed. Here we use S to denote a conceptual planning and $\bar{S}$ for a complete planning.

The assignment of nurses to shifts should adhere to the following constraints (inspired by the rules and regulations of the Dutch health care system [39]): (1) each nurse may work only a single shift per day; (2) each nurse should work not more than a given maximum $D_{\max} \geq 0$ time units on a day; (3) each nurse should work not more than a given maximum $W_{\max} \geq 0$ time units taken over the full horizon; (4) each nurse should work not more than a given maximum number of days $\tau_{\max} \geq 0$ over the full horizon. Here, the number of constraints on the nurse-to-shift assignment is deliberately kept to a (legal) minimum. For example, standard constraints concerning availability and contractual agreements are not considered. The reason for this is to find an ideal team of nurses to fit the conceptual planning (i.e., in terms of team size and skill mix) rather than designing a conceptual planning that suits a predetermined set of nurses. In our approach, we will start with a superset of available nurses N and optimally assign the nurses in N to the shifts in S, with respect to the (yet to be) formulated objective. It is not required to assign all nurses in N; hence, after the nurse-to-shift assignment, we obtain a subset of all assigned nurses denoted by $N^* \subseteq N$.

To summarize, a complete planning is determined by specifying the following for each day $t \in T$:

(a) Selecting an appropriate number of shifts;
(b) Distribute all jobs in J_t over the available shifts and order the jobs to create routes;
(c) Assign nurses (or nurse placeholders) to the shifts.

The complete planning must satisfy the constraints described above. In the following subsections, we discuss the components used to evaluate the performance of the complete planning.

3.2. Continuity of care index

For the nurse-to-shift assignment, we want to establish consistency in the delivery of care to individual clients through continuity of care. As argued in Section 1, we adopt the CCI as a measure for continuity of care [7,14]. To define the CCI for client $k \in K$, let v_k be the total number of visits required by client k over the complete time horizon, and let v_{nk} be the number of times nurse n visits client k. The CCI for client k is defined, for $v_k > 1$, by

$$\text{CCI}(k) = \frac{\sum_{n=1}^{N} v_{nk}^2 - v_k}{v_k(v_k - 1)}, \tag{1}$$

where N denotes the total number of nurses. In case $v_k = 1$, we set $\text{CCI}(k) \equiv 1$. Note that $\text{CCI}(k)$ takes values in $[0, 1]$, where $\text{CCI}(k) = 0$ indicates that there is no continuity of care (all visits of client k are carried out by a different nurse), while $\text{CCI}(k) = 1$ indicates full continuity of care (all visits of client k are carried out by a single nurse).

To gain a better understanding of the CCI, let us consider a scenario where the visits v_k of an arbitrary client k are distributed among the available nurses using a random assignment. To be precise, let $p_n \geq 0$, with $\sum_{n=1}^{N} p_n = 1$, be the probability that nurse n is assigned any of the v_k visits, independent of the assignment of the other $v_k - 1$ visits. Observe that $(v_{1k}, \ldots, v_{Nk})$ then follows a multinomial distribution with parameters v_k and $(p_1, \ldots, p_N)$. Moreover, v_{nk} then has a binomial(v_k, p_n) distribution, hence, $\mathbb{E}v_{nk}^2 = v_k p_n(1 - p_n + v_k p_n)$. Rewriting the expression for the CCI yields

$$\begin{aligned}\mathbb{E}[\text{CCI}(k)] &= \frac{\sum_{n=1}^{N} v_k p_n(1 - p_n + v_k p_n) - v_k}{v_k(v_k - 1)} \\ &= \frac{\sum_{n=1}^{N} p_n + \sum_{n=1}^{N} p_n^2(v_k - 1) - 1}{v_k - 1} = \sum_{n=1}^{N} p_n^2.\end{aligned}$$

It is interesting to observe that in case $p_n = 1/N$ for all nurses, it holds that $\mathbb{E}[\text{CCI}(k)] = 1/N$. Hence, the CCI decreases rather fast when multiple nurses are involved. This shows that it is far from straightforward to obtain continuity of care in any reasonably sized team. Moreover, $\mathbb{E}[\text{CCI}(k)]$ attains its minimal value in this case (see Lemma A.1 in the Appendix for a proof), corresponding to the intuition that if all nurses are equally involved then the CCI attains the smallest value (note that the minimum of $\mathbb{E}[\text{CCI}(k)]$ is not equal to 0 due to the probabilistic nature of the nurse assignment). In Fig. 2, $\mathbb{E}[\text{CCI}(k)]$ is showcased for a stylized example where $p := p_1$, and all remaining probabilities are defined by $p_n = (1-p)/(N-1)$, $n \neq 1$, for various values of N. As expected, Fig. 2 depicts that $\mathbb{E}[\text{CCI}(k)]$ is minimal at $p = \frac{1}{N}$, and increases from that point on to 1, as p approaches 1. Furthermore, in line with intuition, we observe that $\mathbb{E}[\text{CCI}(k)]$ decreases as the number of available nurses N increases.

An appealing property of $\mathbb{E}[\text{CCI}(k)]$ is that it does not depend on the number of visits v_k (and therefore also not on the time horizon over which we measure continuity). In comparison, this is not the case when we consider the unique number of nurses as a measure of continuity of care, as is common in OR literature (see the discussion in Section 1). In particular, consider $U(k) := N - \sum_{n=1}^{N} \mathbb{I}_{\{v_{nk}=0\}}$, i.e., the unique number of nurses that visit client k. Within the same probabilistic context as above, it holds that

$$\mathbb{E}[U(k)] = N - \sum_{n=1}^{N} \mathbb{P}(v_{nk} = 0) = N - \sum_{n=1}^{N} (1 - p_n)^{v_k}.$$

To properly compare $\mathbb{E}[U(k)]$ with $\mathbb{E}[\text{CCI}(k)]$, we apply the transformation $\bar{U}(k) = 1 - (U(k) - 1)/(N - 1)$, so that $\bar{U}(k) \in [0, 1]$, where

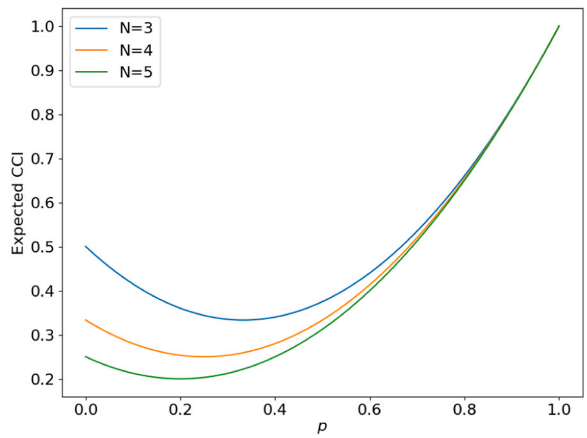


Fig. 2. Illustration of $\mathbb{E}[\mathrm{CCI}(k)]$ as a function of $p := p_1$ and $p_n = (1-p)/(N-1)$, for $n \neq 1$, for various values of N.

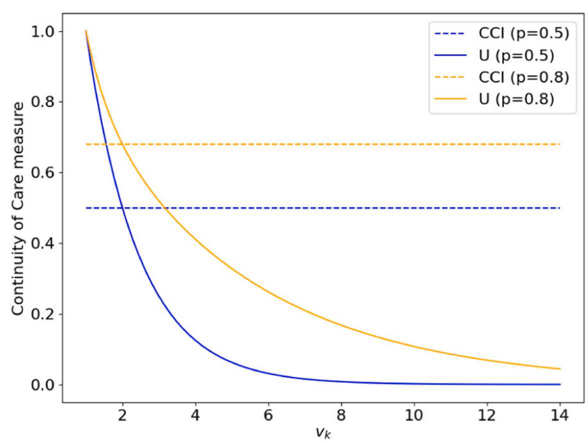


Fig. 3. Comparison of $\mathbb{E}[\mathrm{CCI}(k)]$ and $\mathbb{E}[\bar{U}(k)]$ for $N = 2$, for various values of $p := p_1$ (and $p_2 = 1 - p_1$).

$\bar{U}(k) = 0$ corresponds to the scenario where all visits are carried out by distinct nurses, and $\bar{U}(k) = 1$ corresponds to the scenario where this is done by a single nurse. Fig. 3 illustrates both $\mathbb{E}[\mathrm{CCI}(k)]$ and $\mathbb{E}[\bar{U}(k)]$ as a function of v_k in the case that $N = 2$, for various values of $p := p_1$ (note that $p_2 = 1 - p_1$). Indeed, we observe that $\mathbb{E}[\mathrm{CCI}(k)]$ remains constant, whereas $\mathbb{E}[\bar{U}(k)]$ decreases to 0 in the limit, as the number of visits v_k increases. This shows that for v_k large enough, the probability that both nurses are assigned at least one visit will become close to 1. Hence, even if the majority of visits are assigned to one nurse, counting the unique number of nurses then still suggests that there is no continuity of care.

Remark 1. Instead of analyzing the CCI in a probabilistic context, it is also possible to consider the more 'realistic' situation where the visits v_k of client k are distributed among the nurses without randomness. In this context, p_n is to be interpreted as the proportion of visits from v_k that is directly assigned to nurse n instead of the probability. In this case the number of visits v_{nk} that nurse n makes to client k is deterministic and given by $v_{nk} = p_n v_k$. Consequently, Eq. (1) then reads

$$\mathrm{CCI}(k) = \frac{\sum_{n=1}^{N} p_n^2 v_k - 1}{v_k - 1}.$$

It is noteworthy that as $v_k \to \infty$ we obtain $\mathrm{CCI}(k) \to \sum_{n=1}^{N} p_n^2$. This result is consistent with the expected value of the CCI in the probabilistic context.

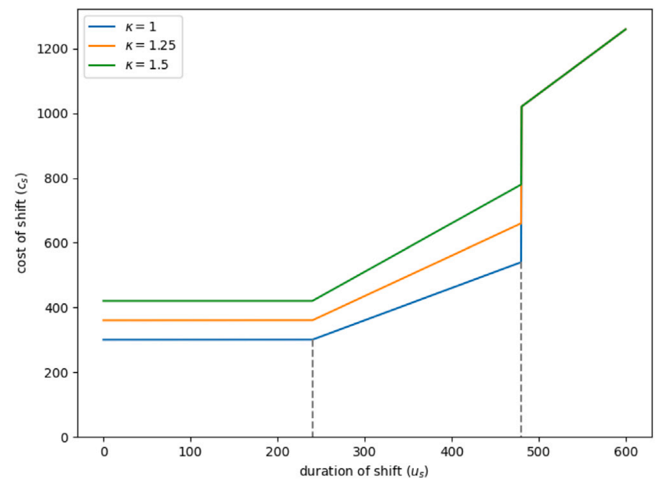


Fig. 4. Example of cost c_s as a function of the shift duration u_s (in minutes), for the values $u_{\min} = 240$, $u_{\max} = 480$, $\kappa_0 = 60$, $\kappa_{\max} = 2$ and various values of $\kappa(\cdot)$.

3.3. Performance evaluation and optimization problem

To evaluate the quality of the complete planning, we define performance measures based on the routes, shifts, and nurse-to-shift assignment. The routes and shifts are evaluated by looking at the daily schedules of the planning, whereas the nurse-to-shift assignment is evaluated by considering all daily schedules of the planning as a whole. The performance measures that we adopt have been found relevant in both practice and literature (see Tables 2–4 in [3] for an overview of widely considered objectives in the literature).

Routes. The routes are evaluated based on their operational quality, which consists of two components: travel time and waiting time. Therefore, the performance measure for the routes within a schedule $S_t \in \bar{S}$ is defined as

$$f_{\mathrm{route}}(S_t) := \sum_{j \in J_t} w_j + \sum_{s \in S_t} \sum_{i,j \in J_t} r_{sij} d_{ij}.$$

Shifts. The shifts are evaluated by the induced costs. Therefore, let $\kappa(q_{n_s}^{(\mathrm{nurse})})$ denote the cost per time unit of a nurse n_s working shift s with a provided qualification level $q_{n_s}^{(\mathrm{nurse})}$. The shift cost c_s for a shift s is defined as

$$c_s := \begin{cases} \kappa(q_{n_s}^{(\mathrm{nurse})}) \max\{u_{\min}, u_s\} + \kappa_0, & \text{if } u_s \leq u_{\max}, \\ \kappa_{\max} u_s + \kappa_0, & \text{if } u_{\max} < u_s < D_{\max}, \\ \infty, & \text{if } u_s \geq D_{\max}. \end{cases}$$

Here, $u_{\min}$ and $u_{\max}$ are the desired minimal and maximal shift durations, respectively. That is, to discourage shifts that are too short, one always pays the cost over $u_{\min}$ time units even when $u_s < u_{\min}$. To discourage overly long shifts ($u_s > u_{\max}$), the cost per time unit is raised to a sufficiently large value $\kappa_{\max} > 0$, whereas exceeding the daily maximum duration $D_{\max}$ is not allowed at all due to the workforce rules and regulations. Finally, $\kappa_0 \geq 0$ represents the startup cost for the shift. In Fig. 4, a visual illustration of the shift cost c_s is given as a function of the shift duration u_s. The performance measure for the shifts on a schedule $S_t \in \bar{S}$ is defined as

$$f_{\mathrm{shift}}(S_t) := \sum_{s \in S_t} c_s.$$

Remark 2. Note that the cost $\kappa(\cdot)$, used to evaluate a shift, depends on the qualification level of the nurse assigned to the shift. However, it is also possible to evaluate a shift if no nurse has been assigned yet. To do this, we simply take the highest required qualification level over all jobs on the shift and set this to be the provided qualification level of the shift. This way, all shifts on a schedule can be evaluated before a nurse assignment has been made.

Continuity of care. The evaluation of the nurse-to-shift assignment is based on continuity of care, as measured by the CCI (see Section 3.2). Hence, the performance measure of the nurse-to-shift assignment over a complete planning $\bar{S}$ is defined as

$$f_{\mathrm{CCI}}(\bar{S}) := \sum_{k \in K} \mathrm{CCI}(k).$$

Objective. Given these performance measures, the quality of a complete planning is evaluated by

$$f(\bar{S}) := f_{\mathrm{schedule}}(\bar{S}) - f_{\mathrm{CCI}}(\bar{S}), \tag{2}$$

where,

$$f_{\mathrm{schedule}}(\bar{S}) = \sum_{S_t \in \bar{S}} (f_{\mathrm{route}}(S_t) + f_{\mathrm{shift}}(S_t)).$$

It is our objective to design a complete planning $\bar{S}$, i.e., perform tasks (a)–(c) described in Section 3.1, while *minimizing* our objective function $f(\bar{S})$.

As the daily HHCRSP is already challenging on its own, the optimization problem stemming from our model is evidently too complex to solve as global optimization problem. Therefore, the global optimization problem is divided into smaller sub-problems, which are then combined into a feasible full-scale solution (i.e., complete planning). Our heuristic-based approach for solving the optimization problem is detailed in Section 4.

Finally, observe that the distribution of jobs (over the available shifts) are fundamental as it provides the main building block for both the route design and the nurse assignment. In this regard, the distribution of jobs needs to accommodate two potentially conflicting objectives, i.e., the planning should be optimal with regard to the daily schedules, while it should also support an appropriate nurse assignment in view of continuity of care. This dual purpose creates a potential trade-off between continuity of care and the quality of the daily schedules. Our heuristic-based approach aims to exploit this dual role of the daily schedule by identifying (partial) routes (i.e., blueprint routes) that are both efficient and allow for continuity of care.

4. Blueprint method

To optimize the objective function f formulated in (2), we proceed in two consecutive steps: first, we design a schedule S_t for each day $t \in T$ to create a conceptual planning, and second, assign nurses to the shifts on the schedules, to complete the planning.

In the first step, the main focus is to minimize f_{schedule}; however, we also need to set up the schedules in support of maximizing f_{CCI} in the second step. To prepare the routes and shifts of the schedules for the second step, we want to exploit sets of regular occurring jobs over the full horizon. To be more specific, it is possible that on multiple days $t_1, t_2, \ldots, t_m$, $m \in \mathbb{N}$, the set of jobs $J_{t_1}, J_{t_2}, \ldots, J_{t_m}$ have significant overlap, which implies that these days are, to a certain degree, similar. On days that share a high degree of similarity, it is useful to have more or less the same routes (i.e., contain the same subset of jobs). This way, jobs that frequently occur on the same days are often grouped together, making it easier to assign the same nurse repeatedly to the same group of jobs (and thus clients) throughout the conceptual planning, which benefits continuity of care. Therefore, we have to guide the day-by-day scheduling process in such a way that it recreates the same routes on days that are similar, given that it maintains the overall quality of the schedules.

With this in mind, our approach consists of the following steps:

1. Cluster all jobs of $\cup_{t \in T} J_t$ into sets of jobs that occur (regularly) on the same set of days.
2. Create 'blueprint routes', i.e., group jobs (within the sets obtained in step 1) into subsets of jobs that need to appear together on a route.
3. Design a conceptual planning by computing a schedule for each day $t \in T$ with respect to minimizing f_{schedule}, while at the same time attempting to recreate the blueprint routes created in step 2.
4. Complete the planning by making a nurse-to-shift assignment that maximizes f_{CCI}.

In step 2, it is important to choose the blueprint routes in such a way that the subsets of jobs that form the blueprint routes are not detrimental to the performance (i.e., f_{schedule}) when we eventually design the actual routes in step 3. In this sense, our blueprint routes should be proper routes and should already be optimized to some extent with respect to f_{route} and f_{shift}. That being said, it is not necessary in step 3 to keep the ordering of the jobs on the blueprint routes intact, although it is probably beneficial to do so.

The complete process of these four steps together will be referred to as the *blueprint method*. The process is illustrated in Fig. 5, where we consider a time horizon of 3 days and two distinct job sets. The jobs in 'job set 1' exhibit a recurring pattern (a result of step 1), with jobs occurring on day 1 and reoccurring on day 3, while the jobs in 'job set 2' span all three days. In contrast, the remaining jobs exhibit no recurring pattern, leading to daily variations within the 'grey set'. In this example, 'job set 2' contains insufficient work to create proper blueprint routes (in step 2). Therefore, the blueprint routes are solely based on 'job set 1'. The shifts, as seen in the conceptual planning (following from step 3), are visually represented by horizontal blocks and are the result of the scheduling optimization conducted concurrently with the recreation of the blueprint routes. Within these shifts, the colored blocks denote the jobs from each job set. In this case, the blueprint routes have been successfully recreated; however, they include additional jobs from other job sets. Finally, the nurses are assigned to the shifts (in step 4), where we note that it is only necessary to assign three of the four available nurses.

The outline of the rest of this section is as follows: Steps 1 and 2 are explained in detail in Section 4.1. Step 3 is described in Section 4.2, where we explain the method to design a daily schedule given the set of jobs J_t. We indicate how the blueprint routes are integrated into the schedule design in Section 4.3. Section 4.4 addresses step 4, focusing on the formulation of the nurse assignment. Finally, in Section 4.5, we introduce benchmark methods to compare to the blueprint method.

4.1. Job clustering and blueprint routes

In step 1 of the blueprint method we group jobs that occur on the same set of days. To be more precise, define for each job $j \in \cup_{t \in T} J_t$ a pattern $\pi_j = (\pi_{j,1}, \pi_{j,2} \ldots, \pi_{j,|T|})$, where $\pi_{j,t} = 1$ if job $j \in J_t$ and $\pi_{j,t} = 0$ otherwise. Hence, π_j shows for each day $t \in T$ whether job j occurs on that day or not. Clearly, two jobs $j, j' \in \cup_{t \in T} J_t$ occur on the same set of days if and only if $\pi_j = \pi_{j'}$. Hence, the first step consists of partitioning the complete set of jobs $\cup_{t \in T} J_t$ into subsets $I_1, I_2, \ldots, I_n$, $n \in \mathbb{N}$, where all jobs in a subset I_k, $k = 1, 2, \ldots, n$, have the same pattern (i.e., $j, j' \in I_k$ if and only if $\pi_j = \pi_{j'}$).

In step 2, we create the blueprint routes. To do this, we partition the jobs within each set I_k into subsets $R_{k,1}, R_{k,2}, \ldots, R_{k,m_k}$, $m_k \in \mathbb{N}$. As mentioned above, our main focus is to make sure that the subsets $R_{k,\ell}$ should already be optimized to some degree with respect to f_{route} and f_{shift}. To obtain such sets, we proceed for each I_k as follows: First check whether I_k contains sufficient work to design at least one proper route, i.e., $\sum_{j \in I_k} p_j \geq u_{\min}$ (note that travel time is excluded in the workload computation as the routes have not yet been established at this stage). If this is the case, design a tentative schedule built on the jobs in I_k (using the scheduling method described in Section 4.2 exclusively on the jobs in I_k). Now, use the jobs on each route from the tentative schedule

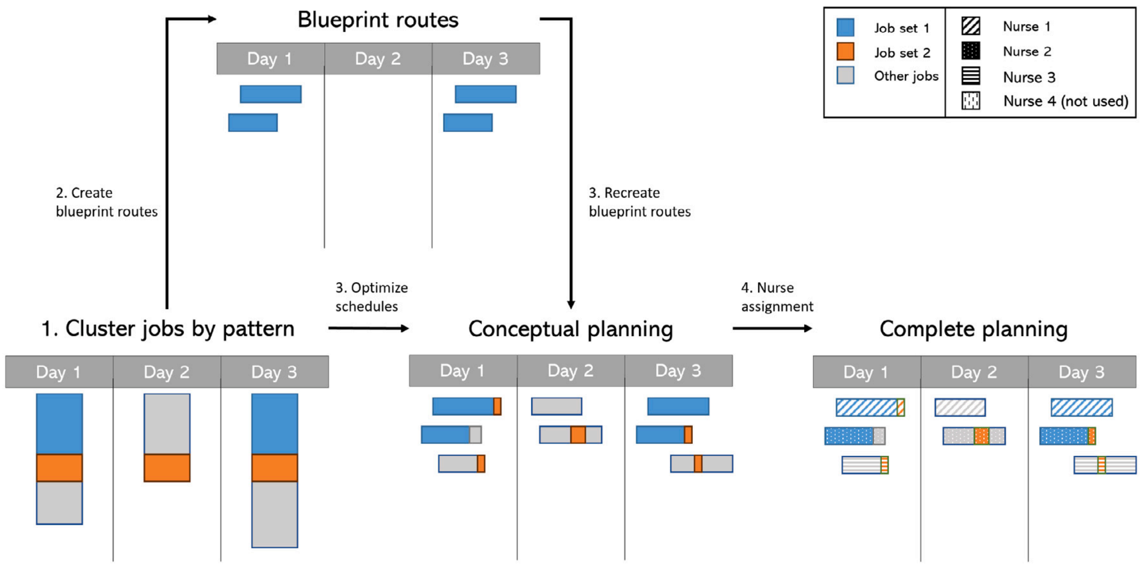


Fig. 5. Example and overview of the blueprint method. Note that job set 2 has insufficient work to create proper blueprint routes and that only three of the four available nurses are assigned.

as a subset $R_{k,\ell}$. Thus, a schedule containing m_k routes yields subsets $R_{k,1}, R_{k,2}, \dots, R_{k,m_k}$. Finally, whenever I_k does not contain sufficient work, no schedule is created, and the next set I_{k+1} is evaluated. The sets $R_{k,\ell}$ are referred to as the blueprint routes. Note that, by construction, all jobs on a blueprint route appear on exactly the same set of days. Finally, denote $\mathcal{R}$ for the set of all blueprint routes.

4.2. Schedule design: paGOMEA

To carry out step 3 of the blueprint method, we consider the problem from the perspective of a single day $t \in T$. That is, to design a schedule S_t given a set of jobs J_t with respect to the performance measure f_{schedule}, which can be regarded as a variant of the HHCRSP. There are many methods available to solve the HHCRSP. We will adopt the recently developed permutation-assignment Gene-pool Optimal Mixing Evolutionary Algorithm (paGOMEA) from [40], which has shown to be effective for HHCRSP. In fact, it is an enhanced evolutionary algorithm which exploits a model-based approach to identify effective sub-solutions. Since it is not our main focus, we will only provide a rough overview of paGOMEA and refer to [40] for details.

On a global level, paGOMEA fits the general framework of a standard evolutionary algorithm (EA). A solution (a schedule in our case) is evaluated with a fitness function (in our case f_{schedule}). The algorithm is initiated with a random population of solutions. Subsequently, the population undergoes a repeated process of exchanging sub-solutions between members of the population (also called recombination) to improve the quality of the solutions with respect to the fitness function. This process continues until the solutions stop improving, or some other stopping condition applies. The effectiveness of the algorithm depends for a large part on the recombination process. In paGOMEA, a model-based approach is used to learn effective sub-solutions on-the-fly from the solutions that appear in the population. This way, effective sub-solutions are kept intact during the recombination process.

The main difference between the current paper and [40] concerns the cost induced by a shift. In particular, in [40] the only performance measure for evaluation of shifts is the so-called shift overtime (i.e., the amount of time that the final completion time on a shift exceeds the corresponding shift duration). In the current paper, shift overtime is dealt with implicitly by penalizing overly long shifts with extra costs. Moreover, there is also the additional startup cost of a shift, which is not present in [40]. As a consequence of the startup cost, in the current paper, there is an incentive to use fewer shifts than the available number of shifts that we input to paGOMEA, whereas in [40] this is not necessarily the case. Finally, in the current paper, we differentiate the cost per qualification level, which encourages paGOMEA to group jobs of the same qualification level into the same shifts. Except for the shift evaluation, the remaining performance measures that constitute f_{schedule} (i.e., travel time and waiting time) are the same as those in [40].

4.3. Conceptual planning by rewarding blueprint routes

To design a conceptual planning, we compute a schedule S_t for each day $t \in T$ which we optimize with respect to f_{schedule} using paGOMEA (see Section 4.2). However, to recreate the blueprint routes in step 3 of the blueprint method, and thereby facilitate continuity of care in the nurse assignment in step 4, we add a reward whenever jobs from a blueprint route in $\mathcal{R}$ are placed on the same shift. Hence, for each day $t \in T$, a schedule S_t is designed with respect to minimizing the adjusted performance measure

$$f_{\text{schedule}}(S_t) - \lambda_1 \beta(S_t), \tag{3}$$

where $\lambda_1 \geq 0$ is the weight of the reward, and $\beta(S_t)$ is the reward defined by

$$\beta(S_t) := \sum_{s \in S_t} \max_{R \in \mathcal{R}} \left\{ |R_s \cap R|^{1+\frac{|R_s \cap R|}{|R|}} \right\}. \tag{4}$$

Here, R_s is the set of jobs that is contained in shift s. The idea behind $\beta(S_t)$ is as follows: each shift $s \in S_t$ contributes to the value of $\beta(S_t)$. The base term $|R_s \cap R|$ counts the number of jobs that are both contained in shift s and the blueprint route R. Meanwhile, the exponent $1 + \frac{|R_s \cap R|}{|R|}$ introduces a bonus factor, rewarding shifts that recreate a larger portion of the blueprint route, given by the fraction $\frac{|R_s \cap R|}{|R|}$. This reward structure thus prioritizes shifts that completely cover blueprint routes, especially favoring larger blueprint routes over smaller ones in terms of job count. Finally, the negative sign in (3) is incorporated because our objective is to minimize this value as part of the optimization process.

4.4. Nurse assignment

In step 4 of the blueprint method we obtain a complete planning $\bar{S}$ from a conceptual planning $S = \cup_{t \in T} S_t$, by assigning a set of nurses

N to the shifts in S. First of all, we suppose that N is sufficiently large to cover all shifts in S and that each nurse can be assigned to each shift (a set of nurses that satisfies $|N| = |S|$ would, for example, suffice). The qualification levels of the nurses are imposed from the complete planning $\bar{S}$ using the method in Remark 2, after the nurse assignment. The idea behind this is to find a set of nurses that best fits the conceptual planning, as mentioned in Section 3.

Problem formulation. To give a mathematical formulation of the nurse assignment, consider the binary decision variable $x_{ns} = 1$ if nurse n is assigned to shift s, and $x_{ns} = 0$ otherwise. The nurse assignment can now be formulated as follows

$$\max \sum_{k\in K} \mathrm{CCI}(k), \tag{5}$$

such that

$$\sum_{n\in N} x_{ns} = 1, \quad \forall s \in S, \tag{6}$$

$$\sum_{s\in S_t} x_{ns} \le 1, \quad \forall t \in T,\ \forall n \in N, \tag{7}$$

$$\sum_{s\in S_t} u_s x_{ns} \le D_{\max}, \quad \forall t \in T,\ \forall n \in N, \tag{8}$$

$$\sum_{s\in S} u_s x_{ns} \le W_{\max}, \quad \forall n \in N, \tag{9}$$

$$\sum_{t\in T}\sum_{s\in S_t} x_{ns} \le \tau_{\max}, \quad \forall n \in N. \tag{10}$$

Here, the constraints in (6) ensure that each shift has exactly one nurse assigned to it, and the constraints in (7)–(10) are the mathematical formulation of the respective constraints given in Section 3.1. Note that constraint (8) is redundant due to the prohibition of nurses from working more than one shift per day as in (7), and the limitation on shift lengths not exceeding $D_{\max}$ (see Section 3.3). Nevertheless, it has been included in the formulation for the sake of completeness.

Remark 3. The mathematical formulation of (5)–(10) can be rewritten as an integer linear program (ILP) by expressing $\mathrm{CCI}(k)$ in terms of x_{ns}. This requires to rewrite the term v_{nk}^2 in $\mathrm{CCI}(k)$ as a sum of binary variables. This can be done by first writing $v_{nk} = \sum_{s\in S} x_{ns}\delta_{sk}$, where δ_{sk} is the number of times client k appears on shift s (note that δ_{sk} is a parameter). With this expression, it holds that

$$v_{nk}^2 = \sum_{s\in S} x_{ns}^2 \delta_{sk}^2 + 2 \sum_{\substack{s_1,s_2\in S\\ s_1\neq s_2}} x_{ns_1} x_{ns_2} \delta_{s_1 k}\delta_{s_2 k}.$$

Since the product of two binary decision variables can be made linear by adding appropriate constraints (see, e.g., [41]), it follows that the problem can be rewritten as an ILP. However, for any problem instance of realistic size (in terms of number of jobs), the computation time for all of the existing solvers makes the ILP impractical.

Solution method. To solve the maximization problem (5)–(10), we make use of a standard EA (see Section 4.2 for a global description of an EA), which is a popular method to solve NRPs, see for instance [30,31]. First, the representation of the solution in the nurse-to-shift assignment is given by a tuple $(n_1, n_2, \dots, n_{|S|})$, where $n_i \in N$ represents the nurse assigned to shift i. For an arbitrary solution, it is possible to violate constraints (7)–(10), but this cannot happen for constraints (6). To ultimately obtain a feasible solution, we penalize any such violation within the fitness function. In particular, we set the fitness function to

$$f_{\mathrm{CCI}}(\bar{S}) - \lambda_2 v(\bar{S}), \tag{11}$$

where $\lambda_2 \ge 0$ is some weight and $v \ge 0$ is the number of constraint violations of the evaluated solution. Note that the negative sign is due to the fact that the optimization is a maximization in this case.

Remark 4. For convenience, in our implementation we used a special case of paGOMEA that is similar to a more standard EA, see [40] for details.

Table 1
Overview of methods (see Remark 5 for an analysis of runtime complexity).

Method	Objective	Reference	Runtime complexity
Blueprint method	$\min f_{\mathrm{schedule}} - \lambda_1 \beta$	(3)	$\mathcal{O}(\lvert T\rvert PG \max_{t\in T} \lvert J_t\rvert^2)$
Baseline method	$\min f_{\mathrm{schedule}}$	(3) (with $\lambda_1 = 0$)	$\mathcal{O}(\lvert T\rvert PG \max_{t\in T} \lvert J_t\rvert^2)$
Dynamic method	$\min f_{\mathrm{schedule}} - \lambda_3 \hat{f}_{\mathrm{CCI}}$	(12)	$\mathcal{O}(\lvert T\rvert PG \max_{t\in T} \lvert J_t\rvert^2)$

4.5. Benchmark methods

To benchmark the blueprint method, we consider two alternatives. The first method compares the blueprint method to a baseline in which schedules are just optimized on a day-by-day basis; we will refer to this as the *baseline method*. The second method is inspired by the approach in [13], where the planning is generated dynamically, using a rolling horizon approach; note that a rolling horizon approach is also employed in [28]. The latter state-of-the-art method will be referred to as the *dynamic method*. The two methods are discussed in somewhat more detail below, whereas an overview of all used methods is given in Table 1.

Baseline method. Recall that the blueprint method designs a schedule for each day $t \in T$, while recreating blueprint routes in the process. This is done to benefit the continuity of care in the nurse-to-shift assignment afterward. To obtain a baseline for the blueprint method, we proceed exactly the same but without recreating the blueprint routes. That is, we optimize the schedules according to f_{schedule} while excluding the reward β during the optimization (i.e., we set $\lambda_1 = 0$ in (3)). Afterward, we still proceed by optimizing the continuity of care in the nurse-to-shift assignment. Hence, compared to the blueprint method, there is no deliberate effort to structure the schedules in such a way that it supports establishing continuity of care in the nurse-to-shift assignment.

Dynamic method. In contrast to the blueprint method, which optimizes the continuity of care indirectly by structuring the schedules beforehand, continuity of care can also be optimized by directly incorporating it into the optimization of the daily schedules. This is done by keeping track of the client configurations based on a rolling horizon. In particular, for a given day $t \in T$, suppose that we have already designed a schedule for each of the previous days $1, \dots, t-1$. The schedule for day t can now be designed with the objective of minimizing the adjusted objective function

$$f_{\mathrm{schedule}}(S_t) - \lambda_3 \hat{f}_{\mathrm{CCI}}(S_t), \tag{12}$$

where $\lambda_3 \ge 0$ is a given weight and $\hat{f}_{\mathrm{CCI}}$ is an adjustment of f_{CCI}. Here, the adjusted function $\hat{f}_{\mathrm{CCI}}$ only takes clients into account that appear in the schedules up to (and including) time t. Note that it is only possible to optimize $\hat{f}_{\mathrm{CCI}}$ by scheduling the jobs J_t on day t, whereas the computation of $\hat{f}_{\mathrm{CCI}}$ also depends on the shift allocations of the clients having jobs on days $1, \dots, t-1$. The optimization of the dynamic method is carried out with paGOMEA on a day-by-day basis, using (12) as the fitness function. In this method, each shift directly corresponds to a nurse (i.e., a shift is not viewed as a placeholder) in order to compute $\hat{f}_{\mathrm{CCI}}$. This approach does not take the nurses' workforce rules and regulations into account, i.e., constraints (8)–(10). To make a fair comparison with the other methods, we reassign the nurses using the nurse-to-shift assignment from Section 4.4 once the schedule is generated.

Remark 5. The runtime for the three methods in Table 1 is of the same order. Specifically, based on the four steps outlined in Section 4, each method involves designing a conceptual planning (i.e., step 3), which utilizes paGOMEA (see Section 4.2) to generate a schedule for each day $t \in T$, based on the jobs in J_t. The runtime for this process on day t is $\mathcal{O}(PG|J_t|^2)$ [40], where P and G are the population size and the number of iterations selected for paGOMEA, and $|\cdot|$ is the cardinality of the set.

Note that larger values of P and G yield better results at the cost of an increase in runtime [40]. Consequently, the total runtime for designing the conceptual planning is $\mathcal{O}(|T|PG\max_{t\in T}|J_t|^2)$ for all methods. Notably, the blueprint method includes an additional preprocessing stage for generating blueprint routes (i.e., step 1 and step 2), which is not necessary for the baseline and dynamic methods. The runtime for this stage is dominated by the scheduling stage. Specifically, clustering jobs by pattern has a runtime of $\mathcal{O}(|T||\cup_{t\in T} J_t|)$, and generating blueprint routes also uses paGOMEA. Finally, the nurse assignment (i.e., step 4) is performed using a variant of paGOMEA (which is independent of the method used), and has a runtime of $\mathcal{O}(PGV^2)$, where V is the number of shifts in the conceptual planning.

5. Numerical experiments

In this section we numerically evaluate the performance of the blueprint method. The model parameters are mainly inspired by data from a partner home care organization, see Section 5.1. The experimental results are presented in Section 5.2.

5.1. Data illustration and generation

For the experiments, a total of 125 problem instances are generated, where each problem instance has a time horizon of one week. This choice was based on the common practice of having a weekly repeating schedule. To ensure a close alignment with practice, the problem instances are constructed by deriving almost all data and parameters from a real-life Dutch care provider, either through bootstrapping or estimation. The Dutch care provider provides home, residential, custodial, personal, and informal care support to roughly 12,000 clients. The underlying data for the 125 problem instances is derived from detailed planning data provided in [40]. In addition, to better understand the care activity frequencies, we used the data in [42], involving all care activities carried out between 2020 and 2021 by one of the 55 teams that provide regular home care. We note that the data from [42] only serves to obtain insights into care activity frequencies. This data is not used for generating the 125 problem instances since it lacks detailed planning data, unlike the data set available in [40], which is from the same care provider.

From the data provided in [42], it is interesting to note that the care activities indeed follow a recurring pattern throughout the week, emphasizing the relevance of continuity of care. This can be observed in Fig. 6, where we depict the number of day parts (i.e., morning, afternoon, and evening) within a week that a specific client receives care. For example, in Fig. 6 we see that roughly 19% of the clients receive care on 7 day parts in a week. This typically corresponds to a care activity (i.e., job) that needs to be performed once every day, such as a daily shower in the morning. We note that a daily recurring job makes it difficult to ensure continuity of care. It is interesting to observe that care activities for clients either occur only a few times per week (1, 2, or 3) or a multiple of 7 times (7, 14, or 21).

Now, the process of generating a single problem instance is as follows:

1. The locations of clients are simulated with a Matérn (cluster point) process (see [43], or [44] for the application of a Matérn process in a vehicle routing context). The Matérn process is a method to simulate randomly located points in a region that tend to form random clusters; we refer to Appendix A.2 for a more elaborate explanation. In our experiments, the region concerns a rectangle with dimensions varying across different problem instances, leading to distinct upper limits for travel time ranging from 5 to 15 min. Let M be the (random) number of (potential) client locations. We set the parameters of the Matérn process such that there are $\mathbb{E}[M] = 100$ client locations per instance. In Fig. 7, we present an illustrative example of a realization from a Matérn process.
2. Each client is allocated a random number of jobs, ranging between 1 and 3 jobs. This allocation is determined using a so-called caseload complexity distribution, which will be explained later in this section. The job allocation is carried out on a per-client basis, where we select the next client at random, ensuring that each client is selected not more than once. As we allocate jobs to clients, we stop this process when the cumulative number of jobs reaches M. Any remaining clients beyond this point are excluded from the instance. Hence, each instance consists on average of 100 jobs, which we observed to be consistent with practical scenarios (note that a job can have multiple occurrences over a week).
3. For each job, we bootstrap/simulate a time window, service time, required qualification level, and a pattern (indicating the recurring pattern of the job over the week) based on the real-life data set from [40]. Evidently, the location of the job corresponds to the location of the client. In Table 2, a statistical summary is presented of the problem characteristics taken over all 125 problem instances, including an indication of whether the parameters are directly based (bootstrapped or estimated) on the real-life data set.

Caseload complexity. The caseload complexity of a client indicates the number of jobs the client has over the given time horizon. When considering the continuity of care, achieving high CCI values presumably becomes more difficult when the caseload complexity is high (i.e., when a client has a high number of jobs). To investigate the effect of caseload complexity on continuity of care, we formulate five distinct scenarios representing varying levels of caseload complexity, ranging from low to high. Let θ_i, $i = 1,2,3$, denote the probability that a client has i jobs; each job may have distinct parameters again as discussed above. The five caseload-complexity scenarios are given in Table 3, where the caseload complexity distribution gradually shifts from $(\theta_1,\theta_2,\theta_3) = (1,0,0)$ to $(\theta_1,\theta_2,\theta_3) = (0,0,1)$. For each scenario, we generated 25 problem instances, yielding the 125 problem instances in total. The average number of clients and jobs per scenario of caseload complexity are presented in Table 4, including the average number of jobs per client, which indicates the difficulty in achieving high CCI values.

5.2. Experimental results

To investigate the performance of the blueprint method against the proposed benchmark methods as described in Section 4.5 (i.e., the baseline method and the dynamic method), we conduct experiments on the 125 problem instances as described in Section 5.1. Recall that the main objective is to design a complete planning (i.e., a weekly schedule including routes, together with a nurse-to-shift assignment) as described in Section 3.1, where the optimization is done in two stages: (i) optimize the schedules while simultaneously preparing the shifts/routes to facilitate continuity of care at the second stage, (ii) after the schedules are created a nurse-to-shift assignment is conducted with respect to optimizing continuity of care.

Parameters. The experiments are performed with the parameters given in Table 5, and are for the most part based on the current Dutch workforce rules and regulations for home care (see [39]). Note that the shift costs, such as $\kappa(\cdot)$, for each qualification level is based on the relative difference in hourly wage.

The weights for the blueprint method and the dynamic method (λ_1 and λ_3, respectively, as also given in Table 1), are carefully specified per problem instance per day to get a balanced trade-off between schedule costs and CCI. In particular, before applying the blueprint or dynamic method, we first obtain the schedule cost on day t of problem instance i using the baseline method, denoted by $\alpha(i,t)$. Subsequently, we set the weights for each problem instance i and day t as follows: $\lambda_1 = \alpha(i,t)/\beta_{\max}(i,t)$ and $\lambda_3 = \alpha(i,t)/\mathrm{CCI}_{\max}(i,t)$. This means that we initially

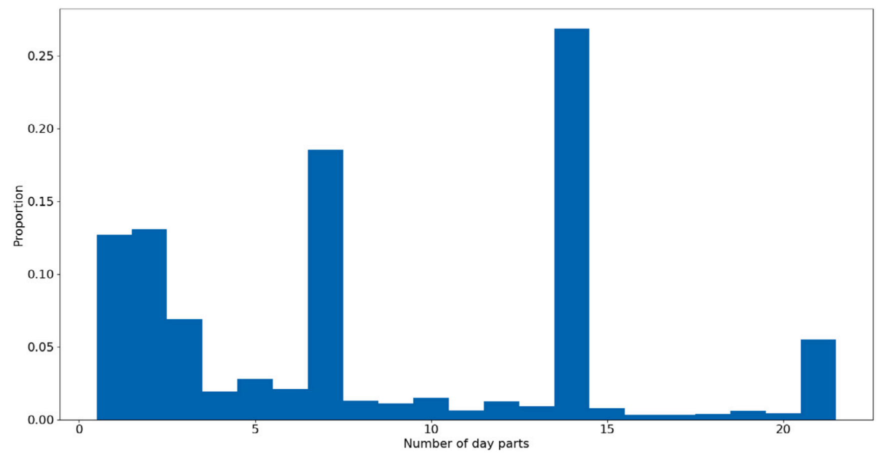


Fig. 6. Number of day parts (i.e., morning, afternoon, and evening) during which a client receives care over the course of a week, based on the years 2020–2021.

Table 2
Statistical summary of problem characteristics taken over all 125 problem instances, with indication whether the parameters are directly based on real-life data from [40]. The travel time concerns the average between each pair of locations.

Variable	Mean	Standard deviation		Based on data
Jobs	98.95	10.83		✗
Job occurrence (days per week)	4.68	2.45		✓
Service time (min)	20.96	12.3		✓
Time window length (min)	72.3	35.99		✓
Travel time average (min)	5.51	1.92		✗
	Low	Mid	High	
Qualification level	87.6%	12.2%	0.2%	✓
	Morning	Afternoon	Evening	
Day part	57%	10%	33%	✓

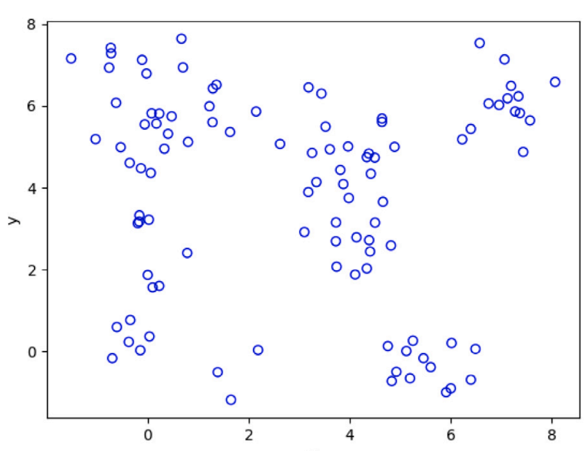


Fig. 7. Example of client (x, y)-locations as the realization of a Matérn process.

Table 3
Caseload complexity distributions for different caseload complexity groups (with θ_i the probability that a client has i jobs).

Caseload complexity	θ_1	θ_2	θ_3
Low	1	0	0
Moderate	6/10	3/10	1/10
Medium	1/3	1/3	1/3
Intermediate	1/10	3/10	6/10
High	0	0	1

Table 4
Average number of clients and jobs per scenario of caseload complexity, including the average number of jobs per client.

Caseload complexity	Clients	Jobs	Job/client ratio
Low	101.08	101.08	1
Moderate	65.96	98.24	1.49
Medium	50.44	99.8	1.98
Intermediate	40.36	101.08	2.5
High	31.84	94.56	2.97

Table 5
Overview of shift-related parameters.

Parameter	Value	Description
$u_{\min}$	240	Minimum shift duration in minutes.
$u_{\max}$	480	Maximum shift duration in minutes.
$\kappa(\text{low})$	1	Cost per minute for a low qualification level.
$\kappa(\text{mid})$	1.25	Cost per minute for a mid qualification level.
$\kappa(\text{high})$	1.5	Cost per minute for a high qualification level.
κ_0	60	Shift start-up cost.
$\kappa_{\max}$	2	Penalty cost per minute of shift overtime.
$D_{\max}$	480	Maximum total shift duration per nurse per day in minutes.
$W_{\max}$	2400	Maximum total shift duration per nurse per week in minutes.
$\tau_{\max}$	5	Maximum days of work per nurse per week.

compute the maximum obtainable reward ($\beta_{\max}(i,t)$) and the maximum CCI ($\mathrm{CCI}_{\max}(i,t)$) for day t of instance i, which are used to scale the weights (see Appendix A.3 for a detailed explanation on deriving $\beta_{\max}(i,t)$ and $\mathrm{CCI}_{\max}(i,t)$). Due to this choice in the objective function, finding an optimal bonus or CCI is considered to be equally important as finding a schedule that is solely optimized regarding schedule costs. Finally, to make sure that the final nurse-to-shift assignment does not

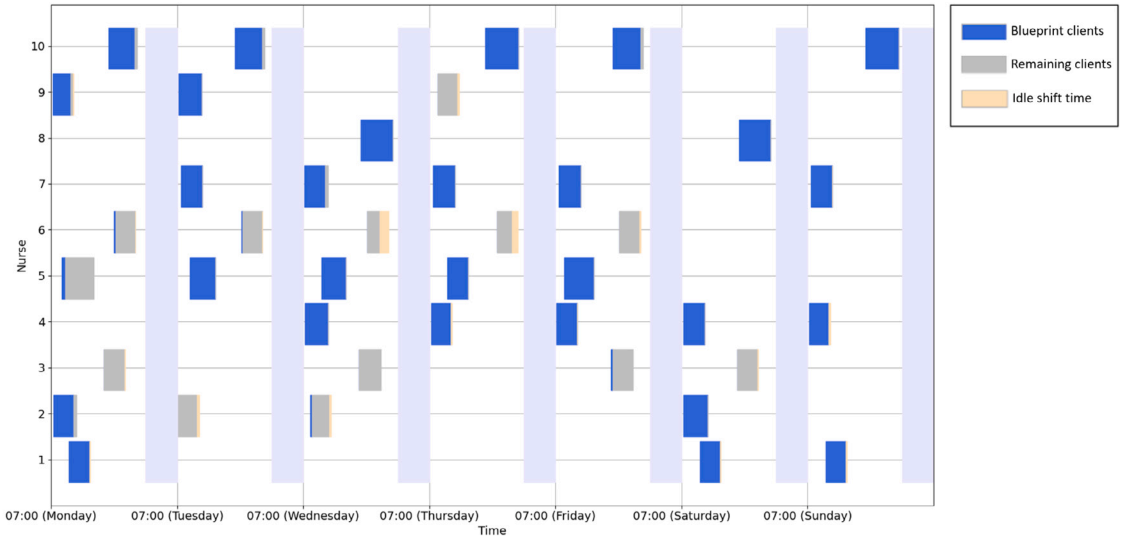


Fig. 8. Example of a solution obtained with the blueprint method for a problem instance with a low caseload complexity.

contain any violations with respect to workforce rules and regulations, the penalty weight λ_2 is set equal to the number of clients on the given problem instance. Hence, one violation is equally important as the hypothetical scenario where all clients have a maximal CCI (note that the CCI has an upper bound of 1). While this penalty system does not guarantee a complete elimination of violations, we observed no violations in the resulting solutions in our experiments.

Results. First, to give an impression of the schedules produced by the blueprint method, Fig. 8 shows an example of the solution of one problem instance with a low caseload complexity. In this example, each block represents a shift, where the length and position of the block specify the duration of the shift and the moment (day and time) the shift takes place, respectively. Furthermore, the blue/gray color scheme of the block signifies the ratio of clients on the shift that is part of a blueprint route (blue) or not (gray). Finally, whenever a shift has a duration that is lower than the minimum duration $u_{\min}$, the corresponding block is augmented with the remaining idle hours (depicted in yellow). From this solution it can be observed that there are 10 nurses required over the span of a week, where the number of daily shifts ranges between 4 and 7 (where Saturday and Sunday require the lowest number of shifts, which is line with the demand pattern). Most shifts have sufficient care activities, such that the minimum shift duration is satisfied without additional (idle) time. We observe a clear distinction with shifts that are either (almost) completely dominated by blueprint clients or shifts that contain hardly blueprint clients. This distinction can also be observed in the nurse-to-shift assignment, with nurses that are predominantly assigned to shifts that mostly include blueprint clients, and nurses that take up the 'remaining' shifts (i.e., shifts that mostly include non-blueprint clients).

In addition to this specific example, we also recorded the shift durations of the complete plannings obtained by the blueprint method for all 125 problem instances, which are depicted in Fig. 9. This figure reveals that most shift durations fall between $u_{\min} = 240$ and $u_{\max} = 480$, with a slight skew towards shorter shifts. Note that the cost structure is designed such that nurses with shifts shorter than 240 are employed based on a shift with length 240. In addition, the shifts are now based only on direct care time and does not include, e.g., non-client related administration time [42], which needs to be incorporated in the final rostering. Hence, the figure indicates that the blueprint method generally creates schedules with balanced shift durations.

The results over all problem instances are presented at an aggregate level in Fig. 10, whereas the comparison per instance can be found in Fig. 11. The average computation times per instance were

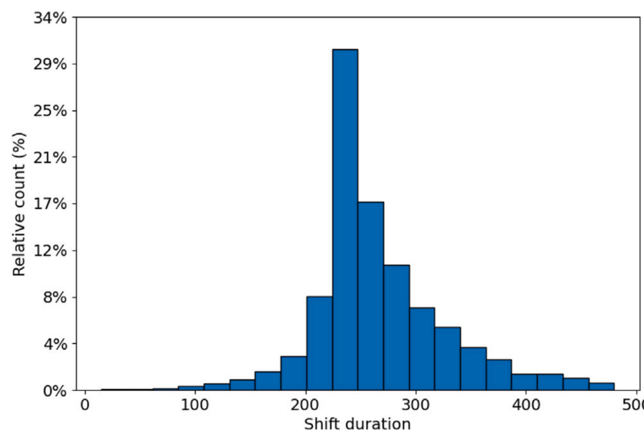
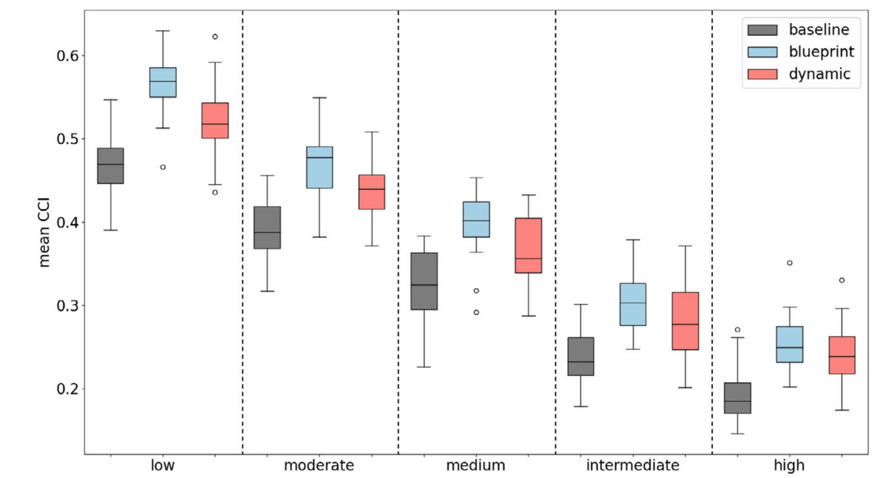


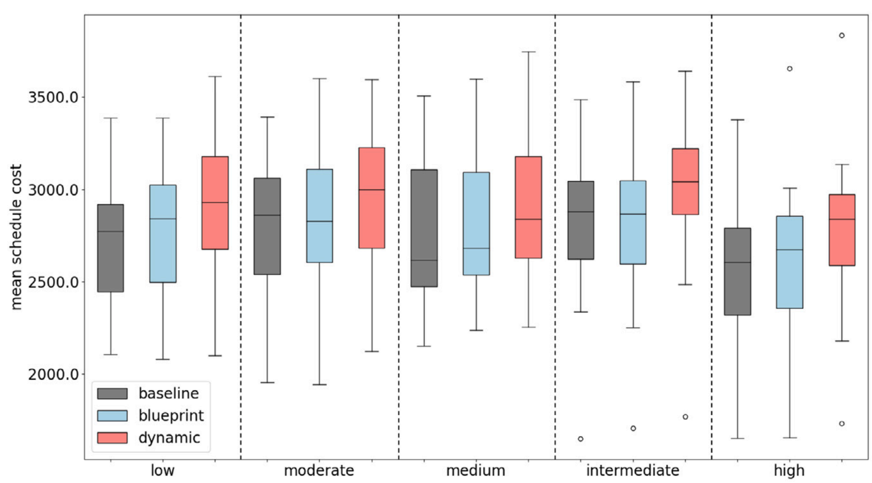
Fig. 9. Shift durations for the blueprint method based on all 125 problem instances.

32 min for the baseline method, 37 min for the blueprint method, and 44 min for the dynamic method, consistent with Remark 5. The algorithms are implemented in Python and the experiments are run on an Intel(R) Core(TM) i5-7200U CPU 2.50 GHz with 8 GB RAM and running on a Windows 10 operating system. Note that the variation in run times is partly due to the variability in paGOMEA. Figs. 10(a) and 10(b) present boxplots of the mean CCI and mean schedule costs, respectively, for each of the three methods. The boxplots are organized by caseload complexity. As can be observed, the blueprint method has the largest mean CCI compared to both the baseline and dynamic method, regardless of the caseload complexity; the additional schedule cost of the blueprint method compared to the baseline method is only marginal. Specifically, the mean relative improvement in CCI between the blueprint and baseline method, taken over all problem instances, is 26%, at a relative increase of 2% in schedule cost. In comparison, between the dynamic method and baseline method, there is a mean relative improvement of 17% in CCI at a relative increase of 7% in schedule cost. As expected, Fig. 10(a) illustrates that the mean CCI becomes substantially lower as the caseload complexity increases for all three methods, whereas the mean schedule cost remains unaffected.

In Fig. 11, the pair-wise comparison between the blueprint, baseline, and dynamic methods are illustrated through scatter plots based on the 125 problem instances. For every combination of methods, each point corresponds to a pair of values (z_1, z_2), where z_i is either the



(a) CCI



(b) Schedule cost

Fig. 10. Boxplots of the three methods grouped by caseload complexity.

mean CCI per client (Figs. 11(a), 11(c) and 11(e)) or the mean daily schedule cost (Figs. 11(b), 11(d) and 11(f)) on a given problem instance for method i. The plane is segmented into an upper segment ($y > x$) and a lower segment ($y < x$), marked by the straight line $y = x$. A point (z_1, z_2) in the upper segment implies that method 2 yields a larger value than method 1 on that particular problem instance, whereas a point in the lower segment implies the opposite.

From Fig. 11(a), it is observed that the blueprint method yields a higher CCI than the baseline method for all problem instances, whereas Fig. 11(c) shows that this is the case for most problem instances when compared to the dynamic method. Fig. 11(e) shows that the dynamic method generally yields a higher CCI than the baseline method, although exceptions exist. Regarding the schedule cost, Fig. 11(b) shows that the blueprint method yields slightly higher schedule cost than the baseline method; however, in some cases the schedule cost turn out to be even lower (this is most likely due to the inherent randomness of the EAs). In comparison, the dynamic method typically yields a higher schedule cost both compared to the baseline method and the blueprint method, as can be seen in Figs. 11(f) and 11(d), respectively.

Finally, we performed a sign test [45] to statistically confirm the pair-wise comparisons, see Table 6 for the results. The statistic in

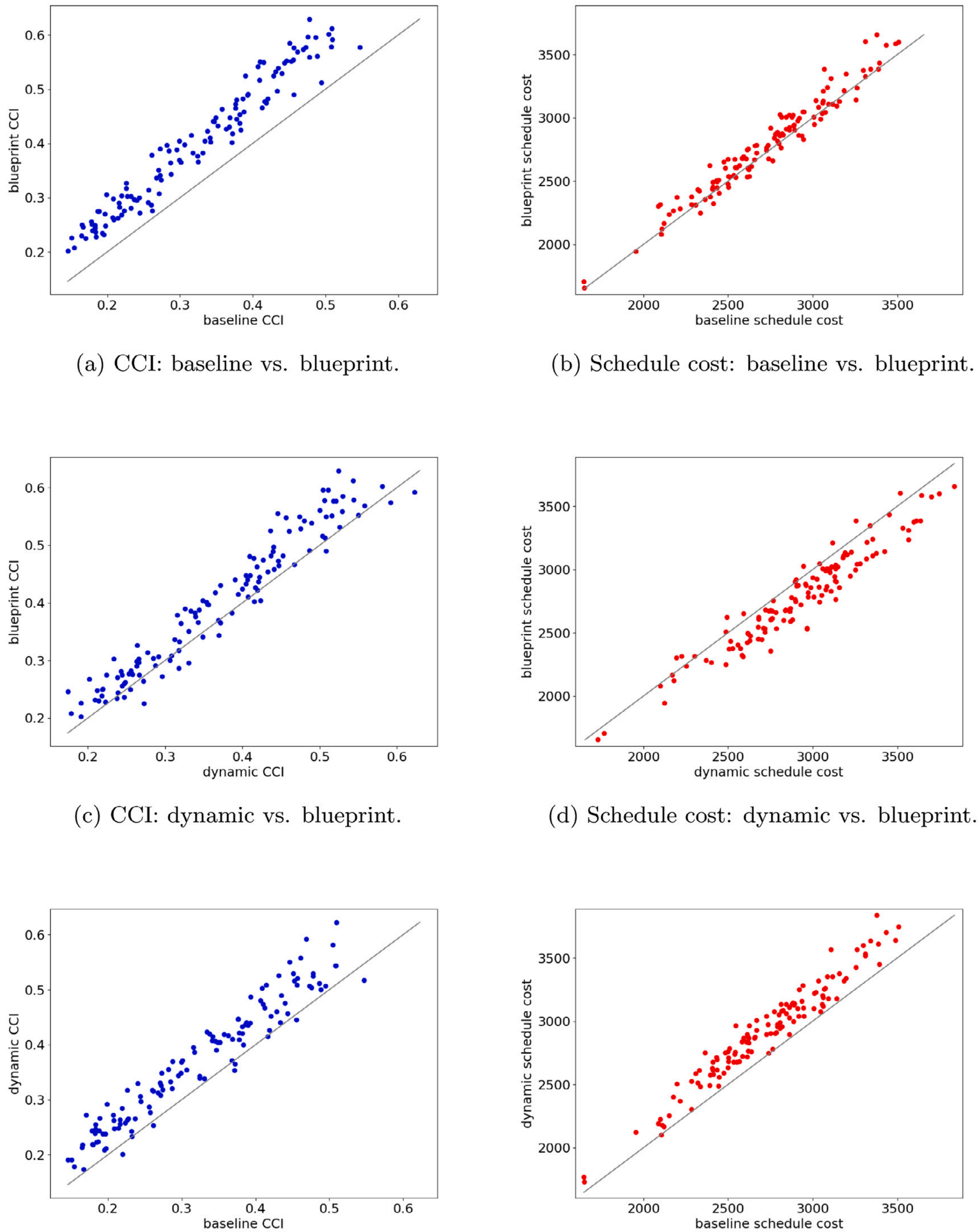
Table 6
Test results from sign test.

Pair	CCI		Schedule cost	
	Statistic	p-value	Statistic	p-value
Baseline vs. blueprint	125	$4.7e^{-38}$	93	$4.36e^{-08}$
Dynamic vs. blueprint	105	$4.13e^{-15}$	14	$6.57e^{-20}$
Baseline vs. dynamic	118	$3.98e^{-27}$	124	$5.93e^{-36}$

Table 6 counts the number of instances where the second method exceeds the first method in value. Under the null hypothesis that the median difference between the results of the selected pair of methods is 0, the statistic follows a binomial distribution with success probability 0.5. Notably, the null hypothesis is consistently refuted (based on $p < 0.025$) across all cases. This means that all comparisons above are statistically significant.

6. Conclusion

Many home care activities occur multiple times per week, placing great importance on continuity of care. In this work, we presented a



(a) CCI: baseline vs. blueprint.

(b) Schedule cost: baseline vs. blueprint.

(c) CCI: dynamic vs. blueprint.

(d) Schedule cost: dynamic vs. blueprint.

(e) CCI: baseline vs. dynamic.

(f) Schedule cost: baseline vs. dynamic.

Fig. 11. Comparison of methods with respect to CCI and schedule cost.

method that is able to generate cost-efficient daily home care schedules and balanced shift lengths while maintaining continuity of care in terms of a well-founded continuity of care index (CCI). The schedules are optimized by constructing shifts and routes that aim to minimize travel time, (time window) waiting time and schedule costs based on hourly wages. The daily schedules are aligned to support the optimization of continuity of care in the nurse-to-shift assignment afterward. This is done by exploiting that care activities (jobs) often have recurring patterns through a novel concept called blueprint routes: pre-optimized (partial) routes that include groups of jobs that have the same recurring pattern. The blueprint routes are then used to guide the scheduling decisions strategically by recreating (parts of) the blueprint routes in the scheduling process. This approach is termed the blueprint method.

The blueprint method is compared to two benchmark methods: the baseline method and the dynamic method. It is observed from the results (based on 125 real-life inspired problem instances) that the blueprint method (significantly) outperforms the baseline method for all problem instances when it comes to continuity of care while compromising the schedule cost only slightly. Moreover, the blueprint method systematically outperforms the dynamic method in both continuity of care and schedule cost. This shows that blueprint routes enable the division of a planning problem over a large horizon while maintaining an overall perspective ensuring continuity of care. The experiments furthermore demonstrate that it is possible to maintain cost-efficient schedules while providing high-quality care to their clients.

In this study, based on the generated weekly schedules, the ideal team composition is determined in terms of nurses and their scheduled working hours. For further research, it is interesting to see whether a blueprint routes-inspired approach can also be effective in a setting of a pre-defined set of nurses. Also, the blueprint method is scalable so that longer time horizons could be considered in future research (possibly using different job clustering approaches or other faster heuristics). Finally, there are many uncertainties in home health care planning, such as travel times, care time, and unforeseen client issues, so it is interesting to study whether the blueprint method can be used as a basis to create more robust schedules.

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CRediT authorship contribution statement

Yoram Clapper: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **René Bekker:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Joost Berkhout:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Dennis Moeke:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Data availability

The data that has been used is confidential.

Appendix

A.1. Minimal CCI

Lemma A.1. *Consider the probabilities $p_n \in [0,1]$, with $\sum_{n=1}^N p_n = 1$, where $N > 0$ is an integer. The sum of squares $\sum_{n=1}^N p_n^2$ is minimal for $p_n = 1/N$.*

Proof. By the Cauchy–Schwarz inequality it holds for arbitrary $\delta_n \in \mathbb{R}$, $n = 1, 2, \dots, N$, that

$$\left(\sum_{n=1}^N p_n \delta_n\right)^2 \leq \left(\sum_{n=1}^N p_n^2\right)\left(\sum_{n=1}^N \delta_n^2\right).$$

Hence, in case that $\delta_n = 1$ for all $n = 1, 2, \dots, N$ it holds that

$$\left(\sum_{n=1}^N p_n\right)^2 \leq N \sum_{n=1}^N p_n^2.$$

Since we assumed that $\sum_{n=1}^N p_n = 1$, it directly follows that

$$\frac{1}{N} \leq \sum_{n=1}^N p_n^2.$$

By choosing $p_n = 1/N$, for all $n = 1, 2, \dots, N$, both sides of the inequality are equal to $1/N$. This shows that for $p_n = 1/N$ the lower bound is sharp, proving the assertion. □

A.2. Matérn cluster point process

Below, we outline how client locations are generated using a Matérn cluster point process, as described in [43]. The Matérn cluster point process is initiated with a set of parent points located within a given region, generated by a (spatial) homogeneous Poisson point process with intensity λ. Each parent has a Poisson distributed number of offspring with mean μ, independently and uniformly distributed in a disk of radius ρ centered around the parent. The outcome of the process is the set of locations of all offspring points (excluding the parent points), which represents the set of clients' locations. In our experiments, the parameter ρ is chosen to be proportional to the maximum possible distance $d_{\max}$ between any pair of points in the region. Specifically, we set the proportionality constant at 20%, yielding $\rho = \frac{1}{2} \times 0.2 \times d_{\max}$.

Now, consider the number of locations M of the Matérn process. Let P be the number of parent points, and C_i be the number of offspring points from parent i. Then, we have

$$M = \sum_{i=1}^P C_i.$$

Due to Wald's identity it follows directly that $\mathbb{E}[M] = \mathbb{E}[P]\mathbb{E}[C_1] = \lambda\mu$. In our experiments, we take $\lambda = 0.2A$, with A the area of the region, such that the number of clusters is proportional to the area size. Moreover, we choose $\mu = 100/\lambda$ such that $\mathbb{E}[M] = 100$. Note that we may also verify that $\mathbb{V}\mathrm{ar}(M) = \lambda\mu(1+\mu)$.

A.3. Maximum reward and CCI

Here we describe how to obtain the maximum reward and CCI, which is used for determining the weights λ_1 and λ_3 (see Section 5.2).

Maximum reward. The maximum reward $\beta_{\max}(i,t)$ on day t of problem instance i can be computed via (3) by considering the following case. Let $\mathcal{R}_{i,t}$ be the set of all blueprint routes of problem instance i that include jobs occurring on day t (recall that all jobs on a blueprint route occur on the same days, see Section 4.1). The maximum obtainable reward is then given by

$$\beta_{\max}(i,t) = \sum_{R \in \mathcal{R}_{i,t}} |R|^2.$$

Note that this corresponds with the scenario in (3) where each blueprint route in $\mathcal{R}_{i,t}$ is completely covered by a distinct shift (i.e., for each $R \in \mathcal{R}_{i,t}$ there is a shift such that $|R_s \cap R| = R$, and there is no shift that covers two blueprint routes).

Maximum CCI. For the maximum CCI on day t of problem instance i (in a rolling horizon setting), i.e., $\mathrm{CCI}_{\max}(i,t)$, we consider the set $K_{i,t}$ of all clients on problem instance i that have a job occurring before or on day t. For convenience, we will omit the index i in the notation below. For a client $k \in K_{i,t}$, let $v_k(d)$ denote the number of required visits of client k on day $1 \leq d \leq t$. In case of a rolling horizon up to day t, it still holds that CCI(k) is maximized when all visits until day t can be carried out by a single nurse, in which case CCI(k) = 1. This may be infeasible, though, in view of workforce rules and regulations. Below, we make the maximum CCI precise for such a situation. Define $\sigma(k,t) := \sum_{d=1}^t \mathbb{I}_{\{v_k(d)>0\}}$ as the number of days until t that client k needs to be visited. In case $\sigma(k,t) > \tau_{\max}$, then client k needs to be visited by at least two nurses. In our case, with a time horizon of one week and $\tau_{\max} = 5$, it is possible to distribute the visits over no more than two nurses. In such a case, the CCI is maximized by assigning one nurse as much visits of the client as possible, whereas the remaining number of visits are assigned to the second nurse. More precisely, let $\mu := \min\{\sigma(k,t), \tau_{\max}\}$ and $\mu^c := \min\{0, \sigma(k,t) - \tau_{\max}\}$, and denote $v_k^{(1)} \leq v_k^{(2)} \leq \cdots \leq v_k^{(t)}$ as the ordered elements of the set $\{v_k(d) : 1 \leq d \leq t\}$. Then,

$$\mathrm{CCI}_{\max}(i,t) = \sum_{k \in K_{i,t}} \frac{\left(\sum_{m=1}^{\mu^c} v_k^{(m)}\right)^2 + \left(\sum_{m'=\mu^c+1}^{\mu} v_k^{(m')}\right)^2 - \sum_{d=1}^t v_k(d)}{\left(\sum_{d=1}^t v_k(d)\right)\left(\sum_{d=1}^t v_k(d) - 1\right)}.$$

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