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Review

Home health care routing and scheduling: A review

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ABSTRACT

In home health care (HHC) operations, nurses are scheduled and routed to perform various services at clients' homes. As this often requires a combination of vehicle routing and scheduling approaches, resulting optimization problems are complex and, hence, of high interest to stakeholders such as researchers, practitioners and policy-makers. With demand for HHC expected to increase substantially, future work is essential to decrease costs and to guarantee service quality. In this review, we provide a comprehensive overview of current work in the field of HHC routing and scheduling with a focus on considered problem settings. Recent advances in HHC optimization are highlighted and future research directions discussed.

Contents

1. Introduction

Population aging and a decrease in informal care are likely to lead to a substantial increase in demand for home health care (HHC) services [51]. In 2011, more than 4.7 million patients received HHC services in the U.S. and of the 12,200 HHC service providers registered, which employed 143,600 full-time equivalents in 2012, around 78.7% were classified for profit [34]. In Europe, between 1% and 5% of the total public health budget is spent on HHC services [31]. An overview of the settings in various European countries is given in Genet et al. [32]. Current risks and trends in HHC are further discussed in Rest et al. [56].

To compete in the market and to lower public expenditures, increasing service quality and decreasing costs are major focus points. Out of this important topic of high public interest originates various challenging optimization problems. Among these, HHC routing and scheduling problems have gained considerable interest over the past years. Considering a wide range of regulative and operational constraints, HHC planners assign nurses to clients and schedule working times. Additionally, travel routes and arrival times of nurses to each client have to be planned. Nevertheless, although these tasks are highly complex, routing and scheduling of

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HHC services are often done manually [26,61,65], resulting in high organizational efforts and potentially sub-optimal solutions. For instance, in a survey on the working time of HHC nurses in two municipalities in Norway, Holm and Angelsen [39] show that driving time accounts for between 18% and 26% of working time, of which 22% of the driving routes were underestimated. This indicates the high potential of optimization in routing and scheduling to improve operations and lower expenses.

Various topics in HHC routing and scheduling are closely related to other research fields. An overview of operations research (OR) methods in health care is given in Brailsford and Vissers [16] as well as in Rais and Viana [52]. Cheang et al. [24] and Burke et al. [19] review nurse rostering. Workforce routing and scheduling problems are investigated by Castillo-Salazar et al. [23] and a computational study is provided. The authors list HHC as one real-world application. A high-level overview on logistical management problems in the field of HHC is given in Gutiérrez and [33] and OR applications in HHC in Vidal [11].

HHC routing and scheduling solution procedures differ substantially as problems considered often originate from different national and regulatory settings. To close this gap, this review provides an overview of work in HHC routing and scheduling. Therefore, an extended definition of HHC is used, which includes various health related services performed at clients' homes such as home care, mobile care and extramural health care, terms which are often used interchangeably in the literature. The focus of this review is set on the routing and scheduling of nurses to clients, whereas the terms 'nurse' and 'client' are used for the remainder of the paper to describe any staff member performing a task or customer receiving a health care related service respectively.

The objective of this review is to compare different objectives and constraints and to further highlight future research directions. To focus on the most relevant work, only published journal articles available online by October 2015 were included. As a consequence, conference publications, book chapters as well as technical reports and working papers are not considered. To derive the list of articles in this review, work containing the terms 'home care' or 'home health care' as well as 'routing' or 'scheduling' in the keywords or abstract was collected. Each shortlisted article was studied in detail and excluded if not within the scope of this review. Hereby, in particular HHC papers which deal with the delivery of medicine or equipment were excluded as the focus of this review is set on the routing and scheduling of nurses. In a final step, the reference sections of the remaining articles were scanned as well as any other articles citing these articles. Additional works of interest were added to the shortlist and again checked for relevant references or citations. Fig. 1 gives a network representation, created with the software Gephi [8], of main topics in the field of HHC routing and scheduling based on selected authors' keywords of the papers reviewed in this work. These include time windows, continuity of care and synchronization issues as well as various solution methods.

Short classifications of selected HHC routing and scheduling papers are found as part of the literature review in Bachouch et al. [4], Gayraud et al. [30], Mankowska et al. [46], Maya Duque et al. [47] and Braekers et al. [15]. These classifications acted as a basis for this work and were verified, merged and extended. The resulting review is structured as follows: Section 2 gives a brief general problem description of HHC routing and scheduling. Section 3 analyzes single-period planning problems, while work on multi-period problems is investigated in Section 4. The review concludes by highlighting promising future research directions in Section 5 and concluding remarks in Section 6.

2. Routing and scheduling of home health care services

HHC planners face complex and challenging optimization problems on different decision-levels, such as shift scheduling, staff assignment and staff routing decisions [33]. In most cases, a set of heterogeneous nurses has to be assigned to heterogeneous clients, who are spread over the operational area. Therefore, various requirements potentially have to be considered, such as matching nurses' skill and clients' requirements, respecting preferences, various regulations as well additional real-world complications of HHC services such as continuity of care or workload balance

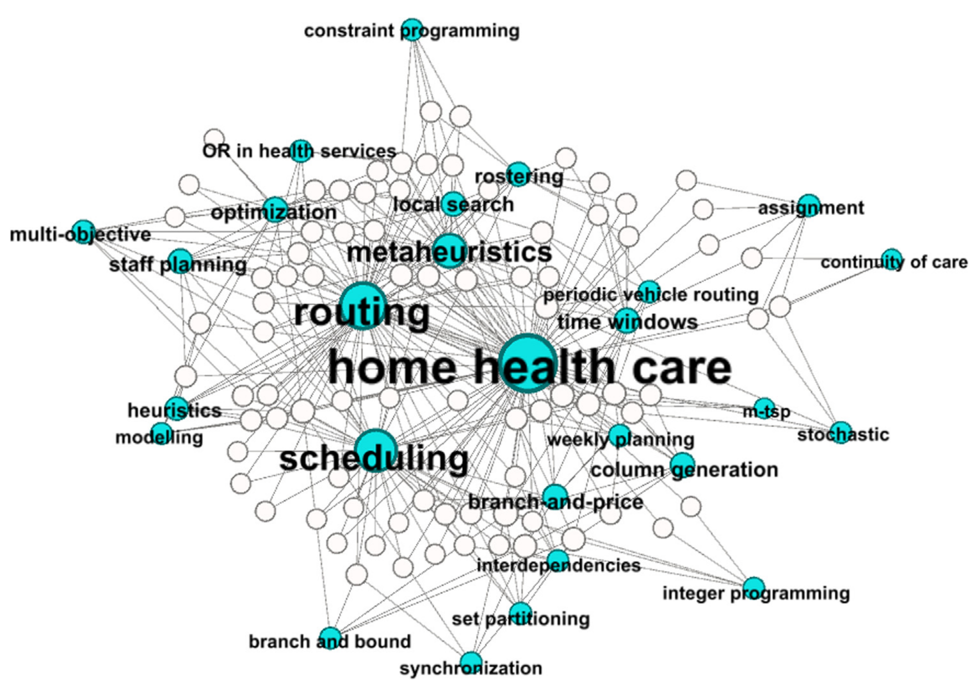

Fig. 1. Visualization of selected author's keywords of the reviewed papers (white circles represent authors; filled circles keywords with the size of the circle representing how often a keyword was included in the sample).

measurements. Additionally, HHC services are often time-sensitive, e.g., insulin injections have to be administered within certain time-frames, which further complicates operations. Implementations of the incorporation of such factors are discussed in detail in the following sections. Typically, a nurse is assigned to multiple clients who can requests multiple services over a certain time period. For a certain planning period ranging from a single day to multiple months, decisions need to be made regarding the order and at what times the clients should be visited. This influences travel distances and working times as well service quality. To plan travel routes and to reach clients, various modes of transport can be used by a nurse, including cars, bikes, public transport and walking.

3. Single-period home health care problems

The majority of research papers focuses on single-period optimization problems, i.e. settings where a single working day is assumed as the planning horizon. In total, this review studied 25 journal publications in the area of single-period HHC problems, which are summarized in Table 1. Therefore, the term matheuristic is used for hybrid methods combining exact solution procedures with heuristics or metaheuristics [3]. Most articles facilitate instances provided by HHC providers; however, as most work differs due to national and regulatory settings, problem formulations vary substantially between the individual articles. As a result, even though multiple authors publish their benchmark instances online, future work is rarely based on existing instances. The reviewed papers are classified and briefly introduced. Differences within the problem settings, objectives and constraints as well as solution methods are investigated in detail in the following subsections.

Early literature: To the best of our knowledge, the problem of routing and scheduling HHC services was first studied in the literature by Fernandez et al. [27], who investigated the working day of community nurses in the United Kingdom. The authors investigated various allocations of nurses to regions and estimated travel times as well as the number of services a nurse can perform. More recently, this work was further extended in Hindle et al. [37,38] with a focus on resource allocation and travel cost approximations respectively. Optimization procedures, which are embedded in decision–support systems (DSS), are presented in Bertels and Fahle [13] and Eveborn et al. [26]. While the former work employs a matheuristic, the latter introduces a repeated matching algorithm to solve the problem. Akjiratikarl et al. [1] model the problem as an extension of the vehicle routing problem (VRP) and apply the metaheuristic Particle Swarm Optimization. Additionally, Bräysy et al. [17] present real-world case studies to show the impact of different scheduling policies.

Temporal precedence and synchronization: In contrast to prior work, Bredström and Rönnqvist [18] highlight the importance and complexity of temporal precedence and synchronization issues in HHC operations. The authors investigate settings where multiple nurses are required to perform a service simultaneously (e.g., to lift over-weighted clients) or multiple nurses have to visit the same client in a given order (e.g., provision of medication before or after lunch). An MIP formulation and a matheuristic as well as

Table 1
Single-period HHC routing and scheduling literature.

Article	Solution method	Instances	Country
Akjiratikarl et al. [1]	Metaheuristic (PSO)	HHC provider	UK
Allaoua et al. [2]	Matheuristic	Kergosien et al. [42] (Randomly generated)	–
Bachouch et al. [4]	Exact	Randomly generated	–
Bertels and Fahle [13]	Matheuristic	Randomly generated	–
Braekers et al. [15]	Exact/Metaheuristic (MDLS)	HHC provider[a]	AT
Bräysy et al. [17]	VRP Solver	HHC provider	FI
Bredström and Rönnqvist [18]	Exact/Matheuristic	Randomly generated	–
Dohn et al. [25]	Exact (B&P)	Airport operator	n.s.
Eveborn et al. [26]	Heuristic (RM)	HHC provider	SE
Fernandez et al. [27]	Approximation	HHC provider	UK
Fikar and Hirsch [28]	Matheuristic	HHC provider[b]	AT
Hiermann et al. [36]	Metaheuristic (VNS/MA/SA/SS)	HHC provider[c]	AT
Hindle et al. [37]	Approximation/Heuristic	HHC provider	UK
Hindle et al. [38]	Approximation	HHC provider	UK
Lanzarone and Matta [45]	Exact	HHC provider	IT
Mankowska et al. [46]	Exact/Metaheuristic (AVNS)	Randomly generated[d]	–
Mısır et al. [48]	Heuristic	Justesen and Rasmussen [41] (HHC provider)	DK
Mutingi and Mbohwa [49]	Metaheuristic (FSEA)	Randomly generated	–
Rasmussen et al. [53]	Exact (B&P)	HHC provider + Bredström and Rönnqvist [18]	DK SE
Redjem and Marcon [54]	Heuristic	HHC provider	n.s.
Rest and Hirsch [55]	Metaheuristic (TS)	HHC provider	AT
Trautsamwieser and Hirsch [61]	Exact/Metaheuristic (VNS)	HHC provider	AT
Trautsamwieser et al. [60]	Exact/Metaheuristic (VNS)	HHC provider[b]	AT
Yalçındağ [66]	Exact/Metaheuristic (GA)	HHC provider + VRP	IT
Yuan et al. [67]	Exact (B&P)	VRPTW	–

(A)VNS, (Adaptive) Variable Neighborhood Search; B&P, Branch-and-Price; FSEA, Fuzzy Simulated Evolution Algorithm; GA, Genetic Algorithm; MA, Memetic Algorithm; MDLS, Multi-Directional Local Search; PSO, Particle Swarm Optimization; RM, Repeated Matching; SA, Simulated Annealing; SS, Scatter Search; TS, Tabu Search; VRP (TW), Vehicle Routing Problem (with Time Windows).
n.s, not specified; AT, Austria; DK, Denmark; FI, Finland; FR, France; IT, Italy; SE, Sweden; UK, United Kingdom.

[a] http://alpha.uhasselt.be/kris.braekers/
[b] http://www.wiso.boku.ac.at/en/production-and-logistics/research/instances/
[c] https://www.ac.tuwien.ac.at/research/problem-instances/
[d] http://prodlog.wiwi.uni-halle.de/forschung/research_data/hhcrsp/

Table 2
Objectives of single-period HHC routing and scheduling problems.

Objective Minimize (↓)/maximize (↑)	TT ↓	TC ↓	TD ↓	WA ↓	OT ↓	PR ↑	#N ↓	CV ↓	FA ↑	#T ↑
Akjiratikarl et al. [1]	–	–	X	–	–	–	–	–	–	–
Allaoua et al. [2]	–	–	–	–	–	–	X	–	–	–
Bachouch et al. [4]	–	–	X	–	–	–	–	–	–	–
Bertels and Fahle [13]	–	X	–	–	–	X	–	X	–	–
Braekers et al. [15]	–	X	–	–	X	X	–	X	–	–
Bräysy et al. [17]	–	–	X	–	–	–	–	–	–	–
Bredström and Rönnqvist [18]	X	–	–	–	–	X	–	–	X	–
Dohn et al. [25]	–	–	–	–	–	–	–	–	–	X
Eveborn et al. [26]	–	X	–	–	–	–	–	–	–	–
Fernandez et al. [27]	–	–	X	–	–	–	–	–	–	–
Fikar and Hirsch [28]	X	–	–	X	–	–	–	–	–	–
Hiermann et al. [36]	X	–	–	–	X	X	–	X	–	–
Hindle et al. [37]	X	–	X	–	–	–	–	–	–	–
Hindle et al. [38]	–	X	–	–	–	–	–	–	–	–
Lanzarone and Matta [45]	–	–	–	–	X	–	–	–	X	–
Mankowska et al.[46]	–	X	–	–	–	–	–	X	X	–
Mısır et al. [48]	X	–	–	X	X	X	–	X	–	–
Mutingi and Mbohwa [49]	–	–	X	–	–	–	–	X	X	–
Rasmussen et al. [53]	–	X	–	–	–	X	–	–	–	X
Redjem and Marcon [54]	X	–	–	X	–	–	–	–	–	–
Rest and Hirsch [55]	X	–	–	X	X	–	–	–	–	–
Trautsamwieser and Hirsch [61]	X	–	–	X	X	X	–	X	–	–
Trautsamwieser et al. [60]	X	–	–	X	X	X	–	X	–	–
Yalçındağ et al. [66]	X	–	–	–	–	–	–	–	X	–
Yuan et al. [67]	–	X	–	–	–	–	X	X	–	–
Sum	10	7	6	6	7	8	2	9	5	2

TT, Travel Time; TC, Travel Cost; TD, Travel Distance; WA, Wait Time; OT, Overtime; PR, Preference; #N, # of Nurses; CV, Soft Constraint Violations; FA, Fairness (Workload Balance); #T, # of Tasks.

numerical experiments are presented. In Dohn et al. [25], a branch-and-price (B&P) framework to schedule simultaneous tasks is proposed. The authors list HHC as an application area, but instances originating from airport operations are used for computational experiments. Bachouch et al. [4] develop an MIP formulation considering shared visits and break nodes. In Rasmussen et al. [53], five different types of temporal precedence and sychronization issues in HHC operations are defined. A B&P algorithm is presented to model such settings. Expanding on the previous works, Mankowska et al. [46] and Redjem and Marcon [54] propose (meta)heuristic solution procedures to handle real-world sized instances. Therefore, Mankowska et al. [46] develop an Adaptive Variable Neighborhood Search while in Redjem and Marcon [54] a two-stage heuristic, which sequentially shifts tasks until all temporal constraints are satisfied, is presented.

Work and break regulations: In Trautsamwieser et al. [60], a Variable Neighborhood Search with a focus on mandatory working and break regulations is proposed. The solution procedure enables multiple shifts and only schedules breaks if a certain working duration is exceeded. To assist HHC providers during times of natural disasters, this work is further extended in Trautsamwieser and Hirsch [61] to investigate the impact of various flood scenarios on the provision of HHC services.

Clustering: A matheuristic, which first clusters the problem by pre-assigning nurses to shifts and then runs an exact method for the routing in each cluster, is proposed in Allaoua et al. [2]. In Mutingi and Mbohwa [49], the authors use fuzzy evaluation techniques to schedule nurses within an evolutionary framework. Therefore, a combination of the consideration of time window preferences, workload balance and clustering efficiency of clients is optimized.

Mode of transport: Most problems assume a single mode of transport (e.g., walking, biking, driving) for nurses to travel to clients. In contrast, Hiermann et al. [36] and Rest and Hirsch [55] consider the additional option of public transport. Therefore, multiple metaheuristics are compared in Hiermann et al. [36], whereas a Memetic algorithm provides the best results. Rest and Hirsch [55] propose Tabu Search variants and further extend the problem formulation by time-dependent travel times and the option to split breaks. To reduce the number of required HHC vehicles, Fikar and Hirsch [28] develop a matheuristic for an HHC transport system. Instead of each nurse operating a separate vehicle, nurses are delivered and picked up by a small bus fleet operated by the HHC provider. This is further combined with the additional option to walk short distances. Results show a substantial reduction in the number of required vehicles and benefits of explicitly considering walking.

Multi-objective: While most work facilitates a weighted objective function to represent different objectives of decision-makers, Braekers et al. [15] develop a metaheuristic solution approach to find a set of Pareto optimal solutions. Therefore, the authors consider two potentially conflicting objectives, the total cost of routing and client inconveniences. As a result, decision-makers are presented multiple solutions and can investigate benefits and trade-offs to derive daily HHC schedules based on individual preferences.

Stochastics: Most articles consider static information, i.e. all data are known in advance and no uncertainty in demands or service times is considered. Real-world operations, however, are stochastic as no perfect information is available. To deal with this circumstance, stochastic demand in HHC operations is studied in Lanzarone and Matta [45] and stochastic service times in Yuan et al. [67]. Both articles develop exact solution procedures. While the objective in Yuan et al. [67] is to reduce a combination of costs and penalties for late arrivals, Lanzarone and Matta [45] aim to generate robust solutions with respect to continuity of care and overtime policies.

Additional topics: Travel time estimations based on historical data to improve nurse assignments are studied in Yalçındağ et al. [66]. A genetic algorithm is developed for a relaxed HHC problem to test the impact of applying Kernel regression techniques. Results show that a two-stage approach, where nurses are first assigned to clients and then routed, leads to similar results as an integrated routing and scheduling approach. Additionally, Mısır et al. [48] investigate generalization of staff routing and scheduling problems by facilitating a hyper-heuristic for the selection of various low-level heuristics. Therefore, the authors consider different problem classes, where an HHC setting is selected to study problems with a daily planning horizon.

3.1. Objectives

Table 2 shows the considered objectives in each of the reviewed articles. As most papers model the problem as an extension of the VRP, travel is the main focus. Nevertheless, in contrast to classical VRP problems where travel distances mostly are minimized [59], in HHC operations, travel cost and travel time are often considered as nurses' working times are the main cost factors. Due to this reason, multiple works further include both overtime and wait times [60,61,36,48]. Additionally, only few procedures explicitly minimize the number of nurses starting a route [2,67]. While employing fewer nurses is clearly an important long-term cost factor, it is not of high importance in single-period planning problems where the number of staff is often fixed. Additionally, this topic is further complicated due to multiple factors in HHC operations such as coverage, service quality and the non-profit status of various providers. Therefore, maximizing the number of served tasks [26,53] is a valid alternative objective for HHC optimization. Nevertheless, in many regulative settings, the provider is required to visit each assigned client, i.e. maximizing tasks is only applicable in competitive HHC settings. Due to such

Table 3
Constraints of single-period HHC routing and scheduling problems.

Article	TW	SK	WT	BK	PR	SZ	UC
Akjiratikarl et al. [1]	X	–	X	–	–	–	–
Allaoua et al. [2]	X	X	–	–	–	–	–
Bachouch et al. [4]	X	X	X	X	–	X	–
Bertels and Fahle [13]	X	X	X	X	–	–	–
Braekers et al. [15]	X	X	X	–	–	–	–
Bräysy et al. [17]	X	–	X	–	–	–	–
Bredström and Rönnqvist [18]	X	X	X	–	X	X	–
Dohn et al. [25]	X	X	–	–	–	X	–
Eveborn et al. [26]	X	X	–	X	–	X	–
Fernandez et al. [27]	–	–	–	–	–	–	X
Fikar and Hirsch [28]	X	X	X	X	–	X	–
Hiermann et al. [36]	X	X	–	–	–	–	–
Hindle et al. [37]	–	–	X	–	–	–	–
Hindle et al. [38]	–	–	X	–	–	–	–
Lanzarone and Matta [45]	–	X	X	–	–	–	X
Mankowska et al. [46]	X	X	–	–	X	X	–
Mısır et al. [48]	X	X	X	–	–	–	–
Mutingi and Mbohwa [49]	X	X	–	–	–	X	–
Rasmussen et al. [53]	X	X	–	–	X	X	–
Redjem and Marcon [54]	X	–	–	–	X	–	–
Rest and Hirsch [55]	X	X	X	X	–	–	–
Trautsamwieser and Hirsch[61]	X	X	X	X	–	–	–
Trautsamwieser et al. [60]	X	X	X	X	–	–	–
Yalçındağ et al. [66]	–	–	X	–	–	–	–
Yuan et al. [67]	X	X	X	–	–	–	X
Sum	20	18	16	7	4	8	3

TW, Time Windows; SK, Skill Requirements; WT, Working Time Regulations; BK, Breaks; PR, Precedence; SY, Synchronization; UC, Uncertainty.

considerations, many publications employ weighted objective functions, which include factors such as respecting client or nurse preferences, various constraint violations, e.g., preferred working time windows and skill assignments, or fairness related issues such as balanced workloads. In contrast, multi-objective solution procedures deriving a set of Pareto optimal solutions [15] are not yet common in HHC routing and scheduling.

3.2. Constraints

In contrast to the objectives, the constraints, categorized in Table 3, differ less between the reviewed articles. Time windows, skill requirements and working time regulations are common factors in most HHC routing and scheduling problems. The specific implementations of such constraints, however, vary substantially between the reviewed articles.

Concerning at what time a service has to be started, most authors consider hard time windows, i.e. no flexibility outside the specified time window. This is a common assumption in HHC operations as many tasks are time-sensitive, e.g., insulin injections or the provision of medication has to be completed during a certain time frame. In addition, soft time windows can be found in a range of articles [13,26,60,61,46,48,67,15], mostly in order to respect client preferences. Therefore, both a hard and a soft time window is given and, if a service is performed outside the soft time windows, a penalty is added to the objective. Additionally, multiple articles set time windows for each nurse [25,2,36,49] to indicate in which time frame nurses can be scheduled to perform services.

Furthermore, matching the skills of nurses and clients is a common feature in HHC optimization and the range of considered skills differs depending on clients' needs and the specific regulative setting. Examples include various medical skills as well as language and social skills. In most of the literature, skill assignments are treated as hard constraints. In Bertels and Fahle [13], however, additional, non-mandatory, skills are included as soft constraints to, e.g., balance the distribution of 'difficult' visits over all nurses. In some cases [60,61,36,28,55], downgrading is further enabled. This indicates that higher qualified nurses are allowed to perform visits that require a lower skill level. While this enables more flexibility in the optimization and allows reducing travel related expenses, additional cost may occur as higher qualified nurses tend to be compensated more for their services. Furthermore, it can severely impact nurses' satisfaction if they are required to perform multiple visits at a lower qualification level. As a consequence, the policy of downgrading is often a common point of discussion for HHC providers. To circumvent this issue, e.g., a maximum number of downgradings per nurse can be implemented [28].

Working time regulations ensure that nurses can only be scheduled for a maximum amount of time and are considered in most of the reviewed articles. Such regulations are often implemented by either setting working time windows or a maximum total distance or duration for each nurse's route. The former strategy is included in Table 3 under *TW* and the latter under *WT*. In the literature, maximum working durations vary from 5 to 10 h. To further respect nurses' working time preferences, multiple authors [60,61,36] consider preferred working time windows and penalize violations in the objective function. In real-world operations, however, working time rosters are often predefined as these have to be planned multiple weeks ahead of the operating day. The impact of such a policy and the possibility of working multiple shifts in a given day is investigated in Rest and Hirsch [55].

Mandatory breaks, e.g., lunch breaks, are less frequently considered. First works in the field [13,26,4] add a predefined mandatory break node, which has to be visited by each nurse. More recent papers [60,61,28] consider if and at what time a break has to be taken, e.g., by setting a maximum cumulative working time without a break. Rest and Hirsch [55] further enable breaks to be split to distribute them over the working day.

Additionally, a range of articles [18,25,53,46,54] focus on the provision of simultaneous services or temporal precedence, e.g., to lift heavy patients or to provide medication before or after lunch. Therefore, a common assumption is that between 10% and 30% of all services are either requiring multiple nurses or have to be performed in a certain order. The implementation of such constraints introduces a high amount of complexity to the solution procedure and, therefore, substantially increases the computational time required to obtain high quality solutions. As a result, instances considering synchronization and temporal precedence commonly include a lower number of nurses and tasks compared to the other reviewed articles.

Similarly, considering uncertainty in single-period HHC operations complicates routing and scheduling activities. The main focus is set on estimating demand [27,45] and its location. Therefore, Lanzarone and Matta [45] distinguish between stochastic demand from patients already assigned to a nurse and new patients. Stochastic service times are considered in Yuan et al. [67]. The authors argue that this is of high importance due to varying health conditions of clients. To model stochastic service times, independent normal distributed random variables for each service are assumed.

3.3. Solution methods

As shown in Table 1, the majority of work develops metaheuristic solution procedures to solve single-period HHC problems. Employed methods are, similar to the studied problem settings, diverse and include various population-based algorithms [1,49,66] as well as local search-based procedures [46,55,15]. Additionally, in Hiermann et al. [36], multiple metaheuristic implementations are compared on a single instance set. In the reviewed papers, real-world based instances with more than 500 nurses and 700 visits are studied [36], however, due to major differences in objectives and constraints, computational comparisons are challenging to derive. Nevertheless, it can be seen that a common assumption for an average single period planning problem of an HHC provider includes approximately 150 visits and 20 nurses. Run times, depending on problem sizes, programming language and computational equipment, vary substantially in the reviewed articles, ranging from a few seconds to up to 75 minutes per instance.

Concerning exact solution procedures, B&P algorithms are predominately implemented [25,53,67]. Therefore, instances with up to 50 clients are solved to optimality within three hours of run time [67]. Additionally, mathematical problem formulations are utilized to benchmark the developed solution procedures with optimization software packages such as CPLEX and Xpress [18,60,61,15]. To combine advantages of exact solution procedures and metaheuristics, multiple authors develop matheuristics, mainly by incorporating set partitioning [2,28] to generate problem clusters and linear programming techniques [13,18,28] to optimize start times and enable synchronization. Additionally, approximation methods [27,38] and heuristics [26,54] are implemented in the reviewed single-period HHC articles.

4. Multi-period home health care problems

Multi-period HHC problems differ from single-period ones as not all service requests arise in the same planning period. As a consequence, nurses may work multiple days and clients request multiple services spread over different days of a week or month. This requires planning procedures to consider a wide range of challenging factors such as complex nurse assignments, working time regulations and continuity of care considerations. In total, this review studied 19 HHC papers with a focus on multi-period optimization problems. The reviewed articles are summarized in Table 4. Solution methods, problem settings and test data differ substantially among the reviewed articles. As a consequence, no commonly accepted benchmark instance set exists. The following part classifies and briefly introduces the reviewed papers. Differences in objectives and constraints as well as in solution methods are elaborated in the following subsections.

Early literature: Based on a real-word case originating in Birmingham, AL, Begur et al. [9] introduce a spatial DSS to assist the planning of HHC services, which includes an MIP formulation to optimize nurses' routes for a five-day routing problem. A client assignment algorithm to balance the workload of nurses under consideration of work and travel times is presented in Hertz and Lahrichi [35]. The authors develop an MIP for a linear objective function and a Tabu Search for non-linear objectives. Additionally, besides studying a single-period problem, Bachouch et al. [4] further consider a planning horizon of five consecutive days.

Multi-stage: In Barrera et al. [7], an MIP to schedule visits of nurses to public schools is presented and results are compared to a two-stage heuristic approach designed for large scale problems. Therefore, a maximum of nine working days is investigated. A two-stage approach is further developed in Nickel et al. [50], which facilitates constraint programming and an adaptive large neighborhood search to generate solutions for two HHC planning problems, namely generating a medium-term master schedule and weekly plans. In contrast, Cappanera and Scutellá [21] investigate the multi-period HHC problem in a joint manner. Expanding on prior work [20], the authors use pattern generation policies within an exact optimization problem to balance workloads of nurses. Therefore, two different objectives are compared, maximizing the minimum nurse utilization factor or minimizing the maximum nurse utilization factor.

Table 4
Multi-period HHC routing and scheduling literature.

Article	Solution method	Instances	Country
Bachouch et al. [4]	Exact	Randomly generated	–
Bard et al. [5]	Exact/Metaheuristic (GRASP)	HHC provider + Randomly generated	US
Bard et al. [6]	Exact (B&P&C)/Heuristic (RHA)	HHC provider	US
Barrera et al. [7]	Exact/Matheuristic	School Health + Randomly generated[a]	CO
Begur et al.[9]	Heuristic	HHC provider + Randomly generated	US
Bennett and Erera [10]	Heuristic	Randomly generated	–
Bennett-Milburn and Spicer [12]	Metaheuristic (MOAMP)	HHC provider	US
Bowers et al. [14]	Heuristic/Simulation (DES)	Midwifery	UK
Cappanera and Scutellá [20]	Exact	HHC provider[b]	IT
Cappanera and Scutellá [21]	Exact	HHC provider[b] +Jensen [40] +Nickel et al. [50]	IT DK
Carello and Lanzarone [22]	Exact	HHC provider	IT
Hertz and Lahrichi [35]	Exact/Metaheuristic (TS)	HHC provider	CA
Koeleman et al. [44]	Heuristic (TR)	Randomly generated	–
Maya Duque et al. [47]	Matheuristic	HHC provider	BE
Nickel et al. [50]	Metaheuristic (ALNS)	HHC provider + Randomly generated	DE
Rodriguez et al. [57]	Exact (SP)	HHC provider	FR
Shao et al. [58]	Exact/Metaheuristic(GRASP)	HHC provider	US
Trautsamwieser and Hirsch [62]	Exact (B&P&C)/Metaheuristic (VNS)	HHC provider[c]	AT
Wirnitzer et al. [65]	Exact	HHC provider	DE

ALNS, Adaptive Large Neighborhood Search; B&P&C, Branch-and-Price-and-Cut; DES, Discrete-Event-Simulation; GRASP, Greedy Randomized Adaptive Search Procedure; MOAMP, Multi-objective Adaptive Memory Procedure; RHA, Rolling horizon algorithm; SP, Stochastic Programming; TR, Trunk Reservation; TS, Tabu Search; VNS, Variable Neighborhood Search.
AT, Austria; BE, Belgium; CA, Canada; CO, Colombia; DE, Germany; DK, Denmark; IT, Italy; UK, United Kingdom; US, United States of America.

[a] http://ftpprof.uniandes.edu.co/~pylo/inst/MCTCSP/instances.htm
[b] http://www.di.unipi.it/optimize/
[c] https://www.wiso.boku.ac.at/en/production-and-logistics/research/instances/

Table 5
Objectives of multi-period HHC routing and scheduling problems.

Objective Minimize (↓)/Maximize (↑)	TT ↓	TC ↓	TD ↓	WA ↓	OT ↓	PR ↓	#N ↓	FA ↑	#T ↑	CC ↑
Bachouch et al. [4]	–	–	X	–	–	–	–	–	–	–
Bard et al. [5]	–	X	–	–	X	–	–	–	–	–
Bard et al. [6]	–	X	–	–	X	–	–	–	–	–
Barrera et al. [7]	–	–	–	–	–	–	X	X	–	–
Begur et al. [9]	X	–	–	–	–	–	–	–	–	–
Bennett and Erera [10]	–	–	–	–	–	–	–	–	X	–
Bennett-Milburn and Spicer [12]	–	X	–	–	–	–	–	X	–	X
Bowers et al. [14]	X	–	–	–	–	–	–	–	–	X
Cappanera and Scutellá [20]	–	–	–	–	–	–	–	X	–	–
Cappanera and Scutellá [21]	–	–	–	–	–	–	–	X	–	–
Carello and Lanzarone [22]	–	–	–	–	X	–	–	–	–	X
Hertz and Lahrichi [35]	–	–	–	–	–	–	–	X	–	–
Koeleman et al. [44]	–	–	–	–	–	–	–	–	X	–
Maya Duque et al. [47]	–	–	X	–	–	X	–	–	–	–
Nickel et al. [50]	–	–	X	–	X	–	–	–	X	X
Rodriguez et al. [57]	–	–	–	–	–	–	X	–	–	–
Shao et al. [58]	–	X	–	–	X	–	–	–	–	–
Trautsamwieser and Hirsch [62]	X	–	–	X	–	–	–	–	–	–
Wirnitzer et al. [65]	–	–	–	–	–	–	–	–	–	X
Sum	3	4	3	1	5	1	2	5	3	5

TT, Travel Time; TC, Travel Cost; TD, Travel Distance; WA, Wait Time; OT, Overtime; PR, Preferences; #N, # of Nurses; FA, Fairness (Workload Balance); #T, # of Tasks; CC, Continuity of Care.

Visiting patterns: In contrast to routing nurses, Shao et al. [58] and Bard et al. [5,6] develop planning procedures for the routing and scheduling of therapists performing sessions at various health care facilities and clients' homes. To optimize routing and scheduling for a single month, Shao et al. [58] present a greedy randomized adaptive search procedure (GRASP) metaheuristic. In Bard et al. [5], this method is extended to allow solving tightly constrained instances. Client requests are defined in both articles by weekly visit frequencies or patterns. In later work [6], a more restrictive problem is considered with fixed visit times. A branch-price and cut (B&P&C) algorithm for small problem instances and a rolling horizon heuristic for larger size problems are introduced.

Working time regulations: A B&P&C algorithm to include a wide range of mandatory break and work regulations, such as lunch breaks and mandatory weekly rest times, is developed in Trautsamwieser and Hirsch [62]. Results of two different variants of the algorithm are compared on real world instances for a single week. A planning horizon of one month is investigated in Wirnitzer et al. [65] through the development of an MIP. Each nurse contracted with a total working time is allowed to work a certain amount of overtime, and rest times have to be observed. A further focus is set on continuity of care as well as compatibility considerations between nurses and clients.

Multi-objective: Multi-objective approaches are developed in Bennett-Milburn and Spicer [12] and Maya Duque et al. [47]. In Bennett-Milburn and Spicer [12], the authors further include the option of assigning some clients to remote monitoring devices. A metaheuristic approach is employed to approximate the Pareto frontier. Maya Duque et al. [47] implement a decision hierarchy in the solution algorithm. A two-stage solution procedure is developed and integrated in a DSS to support real-world operations.

Dynamics: Multi-period HHC routing and scheduling in dynamic settings, i.e. where not all information is known in advance, is studied in Bennett and Erera [10], Koeleman et al. [44] and Bowers et al. [14]. In Bennett and Erera [10], client requests arise randomly in any of the studied periods. These requests have to be visited with a given weekly frequency for a given number of consecutive weeks. Furthermore, the visiting times and visiting days should be kept stable. The authors focus on a single-nurse variant and the planning horizon is defined as 60 days. Similarly, Koeleman et al. [44] study the dynamic assignment of clients. Therefore, a Poisson-distributed arrival rate is considered to simulate the dynamic behavior of the systems. By modeling the systems as a Markov decision process, the objective is to minimize joint costs of rejecting and serving clients. In Bowers et al. [14], a modified Clarke–Wright heuristic is embedded in a discrete-event simulation to investigate the increase in travel time resulting from continuity of care policies. The authors study the setting of community midwifery, where ideally the same nurse performs all visits to a client. Based on a Poisson distributed arrival rate, new clients appear at a random location each day. Results of 30 day-long-simulation experiments demonstrate the impact of preferences, flexible visits and shift patterns.

Stochastics: A stochastic setting with the focus on nurse-to-client assignment and continuity of care is studied in Carello and Lanzarone [22]. To avoid the generation of scenarios, the authors develop a robust cardinality-constrained assignment model to derive schedules. Computational experiments are run with a 26-week rolling time horizon to investigate the impact of stochastic client demand. A stochastic VRP to determine optimal staffing policies in HHC services is investigated in Rodriguez et al. [57]. The authors use a two-stage procedure based on stochastic programming techniques and consider stochastic demand derived from historical data. Additionally, the robustness of solutions is investigated and a Pareto set showing trade-offs between the number of required nurses and the expected coverage of demand is provided.

4.1. Objectives

Table 5 provides a classification of optimization objectives considered in multi-period HHC problems. As shown, the considered objectives vary considerably. While travel related factors are a clear focus in single-period HHC problems, multi-period problems put a greater emphasis on staffing and service related factors. Nevertheless, travel time and related costs are still a main factor in a wide range of papers, especially if the problem is modeled as an extension of the VRP [9,50,5,62]. Additionally, service coverage, overtime, workload balance as well as continuity of care are found to be specific features commonly investigated in multi-period HHC problems.

While Bennett and Erera [10] and Nickel et al. [50] focus on maximizing the number of tasks served, the objective of Barrera et al. [7] and Rodriguez et al. [57] is to serve a given number of requests with the lowest possible number of nurses. Koeleman et al. [44] minimize a combination of rejection and holding costs of clients in the system. Additionally, the minimization of overtime is a major component in multiple articles [50,58,5,6,22]. Therefore, the total overtime over all nurses is summed up in most papers, however, Nickel et al. [50] additionally distinguish between the costs of overtime of each individual nurse based on their qualification level. In Carello and Lanzarone [22], a stepwise function based on different overtime levels for each nurse is introduced to associate higher costs with higher overtime values.

While reducing overtime is imperative due to the high cost related to scheduling nurses longer than contracted, giving each nurse a certain minimum working time is also often of high importance for multi-period HHC routing and scheduling procedures. As a consequence, multiple articles [35,7,12,20,21] include workload balance measurements in the objective function. Hertz and Lahrichi [35] associate each job with a 'heaviness' weight and consider travel, case and visit loads to evaluate the workload of each nurse. In Barrera et al. [7], the difference between the maximum working time and the minimum working time over all nurses is minimized, while Cappanera and Scutellá [20,21] calculate a utilization factor for each nurse based on the scheduled working hours. Bennett-Milburn and Spicer [12], in contrast, focus on the number of assigned clients for each nurse over the planning horizon and calculate pairwise differences between nurses for these assignments.

In contrast to workload balance, most authors model continuity of care in a similar way. Therefore, the total number of different nurses that visit the same client during the planning horizon is commonly minimized [50,12,14]. Additionally, Carello and Lanzarone [22] distinguish between three different classes of clients, namely clients who require hard, partial or no continuity of care. In Wirnitzer et al. [65], minimizing how often the nurse attending has been changed compared to the previous visits is further investigated.

Considering the implementation of the various objectives, most articles model the problem with weighted objective functions. Work on multi-objective optimization is limited to Barrera et al. [7], Bennett-Milburn and Spicer [12], Maya Duque et al. [47] and Rodriguez et al. [57]. In Barrera et al. [7], a lexicographic order is implemented to first minimize the number of nurses and, in a second step, to balance workload. Bennett-Milburn and Spicer [12] distinguish between three conflicting objectives, travel cost, consistency of care and workload balance of nurses, and approximate the Pareto optimal frontier. Results indicate that achieving workload balance is easier than achieving a high level of continuity of care at low travel costs. Similarly, Rodriguez et al. [57] approximate the Pareto frontier to show the trade-offs between coverage and resource costs. In contrast, Maya Duque et al. [47], who aim to maximize service level and minimize distance traveled, develop a two-stage procedure, which optimizes solutions based on lexicographic ordering. The main motivations for this solution strategy are that, according to the authors, HHC planners prefer a single solution and equal standards among HHC regions.

4.2. Constraints

Table 6 classifies the constraints of the reviewed multi-period HHC articles. Time windows, skill requirements and working time regulations are main factors in the majority of multi-period research articles. Additionally, in contrast to single-period HHC problems, continuity of care and uncertainty issues gain considerable attention in multi-period problems.

Table 6
Constraints of multi-period HHC routing and scheduling problems.

Article	TW	SK	WT	BK	CC	UC
Bachouch et al. [4]	X	X	–	X	X	–
Bard et al. [5]	X	X	X	X	–	–
Bard et al. [6]	X	X	X	X	–	–
Barrera et al. [7]	X	–	–	–	–	–
Begur et al. [9]	X	X	X	–	–	–
Bennett and Erera [10]	X	–	X	–	–	X
Bennett-Milburn and Spicer [12]	–	–	X	–	–	–
Bowers et al. [14]	–	–	X	–	–	X
Cappanera and Scutellá [20]	–	X	X	–	–	–
Cappanera and Scutellá [21]	X	X	X	–	X	–
Carello and Lanzarone [22]	–	X	X	–	X	X
Hertz and Lahrichi [35]	–	X	–	–	–	–
Koeleman et al. [44]	–	–	–	–	–	X
Maya Duque et al. [47]	X	X	X	–	X	–
Nickel et al. [50]	X	X	X	–	–	–
Rodriguez et al. [57]	–	X	X	–	–	X
Shao et al. [58]	X	X	–	X	–	–
Trautsamwieser and Hirsch [62]	X	X	X	X	–	–
Wirnitzer et al. [65]	–	X	X	–	–	–
Sum	11	14	14	5	4	5

TW, Time Windows; SK, Skill Requirements; WT, Working Time Regulations; BK, Breaks; WB, Workload Balance; CC, Continuity of Care; UC, Uncertainty.

Concerning the provision of services at clients' homes, visiting patterns are of high interest when dealing with multi-period problems. While some authors [9,12,6,62] assume fixed service days for clients, e.g., client A has to be visited on Monday and Thursday, other articles [10,58,50,47] assume service frequencies as input for the optimization procedures, e.g., client A needs to be visited three times a week. To model frequencies, predefined service combinations are often implemented. In Maya Duque et al. [47], visits further have to be evenly distributed over the working week to guarantee that a minimum time interval is respected between two services for the same client. A similar approach with a minimum required time between two tasks is further implemented in Trautsamwieser and Hirsch [62] and Wirnitzer et al. [65] to model mandatory rest times for nurses between multiple working shifts.

In addition to the articles that consider continuity of care as an optimization objective, various authors further consider this factor with specific soft and hard constraints. In most cases, this is modeled by enforcing that a client has to be visited by the same nurse [4,22,47] or by a maximum number of different nurses [21] during the planning horizon.

Due to the longer planning horizon and the corresponding uncertainty in planning, stochastic and dynamic problems settings receive considerably more attention in multi-period than in single-period HHC optimization. All of the reviewed articles which include uncertainty in their model [10,44,22,14,57] consider stochastic or dynamic demand. Stochastic service or travel times is not found in any of the reviewed articles.

4.3. Solution methods

To solve multi-period HHC problems, as shown in Table 4, the reviewed articles focus on both metaheuristic and exact solution procedures. In contrast to single-period problems, where multiple works implemented population-based algorithms, construction-based [58,5] and local search-based [35,50,12] procedures prevail in the reviewed literature. Implemented exact solution procedures focus on B&P&C [6,62]. Furthermore, integer programming [4,20,21,65], stochastic programming [57] as well as exact robust optimization [22] techniques are employed. Additionally, due to a degree of uncertainty in multi-period HHC operations, a focus is set on the consideration of dynamic events such as new patients requests or required visiting frequencies [10,44,14,57]. Therefore, Monte Carlo simulations [22,57], Markov decision processes [44,22] and discrete-event simulations [14] are facilitated, often in combination with exact or heuristic solution procedures. Investigated planning horizons range from five days to one year. Consequently, problem sizes, computational complexity and run times vary substantially with real-world problem sizes of more than 40 nurses and 4000 visits per month studied in a home care rostering problem [65].

5. Discussion and future research directions

As shown by the reviewed articles, HHC routing and scheduling covers a wide range of interesting research questions with practical implications for HHC providers, policy makers and society. Work within the field differs substantially and solution procedures are mostly tested on instances originating from real-world operations. Even though some instances are available online, no commonly accepted benchmark set exists. Furthermore, as each work differs slightly in the considered objective or constraints, computational comparison is difficult. The following future research directions can be derived from this analysis and indications from industry partners.

Stochastic HHC routing and scheduling: While multiple articles focus on stochastic settings in weekly HHC problems, only Lanzarone and Matta [45] and Yuan et al. [67] deal with a stochastic setting in daily operations. This is quite surprising as daily operations within HHC are severely affected by variations in service durations at clients. Additionally, emergencies may occur requiring a nurse to stay longer at a client or services may be canceled at short notice if a client is transferred to a hospital. Other common issues are sudden unavailability of nurses or delays resulting from traffic congestion. As some services at clients are highly time-sensitive, e.g., the provision of insulin injections, delays may result in severe consequences for the clients and providers. To deal with all this uncertainty, future work on stochastic HHC routing and scheduling is required to enable robust operations.

Integrated multi-stage multi-period planning approaches: As described in Begur et al. [9], HHC planning often consists of multiple planning stages. On a high aggregated level, a long-range master plan is developed to specify the number of nurses and their working time windows. Subsequently, based on this plan, client visits are assigned to a specific day and, finally, nurses are routed and the order of visits is fixed. Sub-optimal decisions on a long-term plan directly influence the optimization potential closer to the day of service. For instance, as discussed in Rest and Hirsch [55], if the long-range master plan results in a lower flexibility of nurses' working times on a specific day, routes may be considerably longer. This connection between the different planning stages highlights the potential of integrated multi-stage and multi-period planning approaches; however, such methods are uncommon in the literature and practice.

Multimodality and mode of transport choices: Most work focuses on single modal transport, i.e., cars, bikes or walking and does not allow combining multiple modes of transport on a given day. Furthermore, as shown in Hiermann et al. [36] and Rest and Hirsch [55], public transport plays an important role in urban city centers. In real-world operations, however, combined modes of transport as well as resource sharing strategies occur frequently. For instance, a vehicle is parked near a major public transport hub by a nurse after completion of a shift. The vehicle is then utilized by the subsequent nurse for the following shift, thus increasing vehicle utilization and lowering vehicle-related expenses. Furthermore, walking short distances instead of driving can be beneficial [28,29], especially if parking spots are limited. These examples show that combining modes of transport is highly beneficial to improve operations and to decrease expenses. Therefore, the development of new solution procedures or the extension of current ones is crucial to enable optimization in such settings.

Sustainability considerations and acceptance of HHC optimization: The current focus in the literature is to reduce cost or travel times under various operational constraints. Innovative mobility concepts for HHC staff can combine different transport modes and may lead to a more sustainable operation of HHC services, e.g., through reduced emissions or less stress for the HHC workers. Current work often lacks the inclusion of ecological and social criteria and, hence, does not take into account all three pillars of sustainability: economic, ecological and social factors [63]. Voegl and Hirsch [64] evaluate sustainability criteria for the mobility of HHC staff and identify approximately 130 different criteria. In the acceptance of HHC planning procedures, one common field of conflict is between efficiency of operations and client-centered approaches [43]. Potential conflicts include additional administrative efforts for nurses as well as time pressures resulting from HHC routing and scheduling. To improve acceptance and implementations of optimization methods, a closer consideration of such social factors in the development process of software systems and solution procedures is required.

6. Conclusion

This review has surveyed literature on HHC routing and scheduling, a field that has received increased attention in recent years due to multiple operational considerations and the high importance of such services to the public. A classification of journal articles is included that focuses on the considered objectives and constraints. Therefore, single-period and multi-period HHC problems are differentiated. The results highlight that this research field is highly heterogeneous in terms of the different focus areas, objectives studied and the considered regulative settings. Most work focuses on static single-modal, single-period problems and is closely related to the VRP. Commonly considered constraints include time windows, skill requirements and working time regulations. Recently, a higher focus is set on synchronization constraints, the consideration of breaks, various preferences of clients and nurses as well as workload and continuity of care measures. Nevertheless, numerous research questions of importance are still to be investigated. These include robust settings, integrated multi-stage methods and the implementation of various and combined modes of transport. Furthermore, the development of sustainable solutions as well as studies investigating the means of acceptance of HHC optimization procedures is of high interest to enable transferal of results to providers.

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