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A multi-agent system based on reactive decision rules for solving the caregiver routing problem in home health care

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abstract

Home Health Care (HHC) services are growing worldwide. HHC providers that employ their caregivers have to manage operational decisions such as assigning patients to caregivers and planning the caregivers' routes. Centralized "off-line" approaches are generally used to deal with both these problems. In this paper, we solved the caregiver routing problem in a dynamic and distributed way using a Multi-agent system (MAS) to simulate caregiver behavior. Four decision rules were developed for the caregivers: NPR (Nearest Patient Rule), NRR (No-wait Route Rule), SRR (Shortest Route Rule), and BRR (Balanced Route Rule). These decision rules were implemented and tested on a multi-agent platform to assess their performances. We designed an experimental plan based on case studies that represent different sizes of HHC provider inspired from real-world examples. The results obtained show the relevance of using local decision rules to plan the caregiver's route.

1. Introduction

Over the last decade, Home Health Care (HHC) services have significantly increased [1]. HHC provides care outside hospital by a team of medical professionals and is presented as an alternative to traditional hospitalization. HHC offers intensive support and care such as daily living services, complex care services, and social and psychological assistance. Patients generally require HHC following a stay in hospital because they still require acute medical care.

The organization of HHC involves two main issues: "medical" decisions and "organizational" decisions. This paper considers the second issue and, more precisely, operational management problems related to human and material resources scheduling. In this case, HHC managers have to solve two operational-level sub-problems: (1) patient-caregiver assignment (denoted "assignment problem") and (2) determining the caregiver's route (denoted "routing problem"). For each patient admitted, solving the assignment problem consists in allocating a caregiver for each care service required while respecting certain constraints (caregiver's skills, order of care, caregiver's availability, etc.) [2]. The caregiver routing problem involves defining the most suitable route for each caregiver to visit assigned patients while minimizing certain factors (waiting time, travel distance, etc.), and taking into account constraints linked to the other caregivers [3,4].

The assignment and routing problems are generally large, complex problems because of the human resources and patients involved, the type and quantity of care received by patients, and the temporal dependency between the care activities

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and the human resources. In addition, unexpected events can occur resulting in uncertainty and disruptions requiring action in real-time. Typically, traffic jams, road accidents, and weather conditions should be taken into account when designing a real-world routing problem [5]. In this context, HHC managers need decision support systems capable of solving large real-world situations in reasonable time and providing good solutions in a dynamic environment with numerous time constraints [6].

To meet HHC managers' expectations, this paper addresses the "routing" problem in a dynamic context with uncertainties and random events. The main contribution of this paper is to provide a new way of solving a large caregiver routing problem using the caregiver's ability to dynamically design his own route. The proposed approach was simulated to demonstrate its performance according to five properties: efficiency, pertinence, scalability, robustness, and implementability.

The remainder of the paper is organized as follows. A literature review is presented in Part II. In Part III, a global framework is described to solve the problems considered. The dynamic routing problem and the four decision rules used by the caregivers to choose their next patient are detailed in Part IV. The multi-agent simulation platform used to assess the performance of the proposed approach and the simulation protocol are presented in Part V. The simulation results are presented and discussed in part VI. Part VII highlights the relevance of the proposed decision rules. Finally, our conclusions and some future lines of research are provided in the last section.

2. Literature review

As mentioned in the introduction, two operational-level sub-problems have been identified: (1) the "assignment problem" and (2) the "routing problem". The literature related to "assignment" and "routing" problems in HHC has been enriched over the last few decades and has recently been reviewed [7,8]. These reviews highlight a large number of papers from the Operational Research community and their main subject is the optimization of the daily planning of health care services with the hypothesis that the patient care plan is the same each day. Related studies suggest different ways of solving these problems based on MILP [9,6] or original heuristics [10–12]. Recently, Nickel et al. [13] propose a heuristic to address the medium-term and short-term planning problem. In other studies, authors have focused on one of the two sub-problems in particular. Yalçındağ et al. [4] focus on the assignment problem, but travel time estimators were added to the model to take routing plan constraints into account. Lanzarone and Matta [2] define an assignment policy based on the cost of home care services. Hertz and Lahrichi [14] propose two MILP-based approaches to assign caregivers to patients in Canada, of which the aim is to balance the workload of the nurses and avoid long journeys. Lanzarone and Matta [15] propose a new assignment approach to cope with random events such as new patient demands and nurse workload. In the literature, the routing problem is largely tackled as a "Travelling Salesman Problem with Time Windows (TSPTW)" approach for designing the caregiver's route using MILP [3] and/or heuristic [16,17] approaches for a static, deterministic problem. The main limitation of these approaches is the computational time required to reach a solution, and in most cases, it is hypothesized that the routing problem is static and deterministic. The decisions are made in an off-line centralized manner with no feedback from real-time situations. No on-line decisions can be made to cope with unexpected events.

The literature review in [18] presents multi-agent systems as an alternative to solve optimization problems in distributed, complex, large, and heterogeneous contexts. The Multi-Agent System paradigm allows distributed approaches to be modeled where several entities (requesters) require services from other entities (providers). In the field of Home Health Care, for example, requesters would be patients and providers would be caregivers. In recent years, MAS have gained tremendously in popularity, providing solutions to transport planning and scheduling problems in healthcare systems in general, and in the management of home health care operations in particular. Recently, Bichindaritz et al. [19] presented advanced methodologies and case studies in health care using MAS and artificial agents. In the field of home care, the project K4Care (Knowledge-Based HomeCare eServices for an Ageing Europe) must be more particularly highlighted [20,21]. This project aims to improve assistance for elderly patients suffering from chronic diseases or disabled persons. A multi-agent system constitutes the heart of the K4Care platform and deals with problems such as negotiation of meetings and task assignment for care providers. More recently, [22] considered home-care staff scheduling and task assignment decisions in a dynamic context with conflicting objectives. The authors propose a system framework incorporating intelligent agents to represent the various actors (manager, supervisor, patient, nurse, resource, and scheduler), internet services, wireless networks, and mobile devices. The different agents in this model are controlled by a manager agent located in the home health care center and there is no direct interaction between caregivers and patients. The software platforms of these MAS approaches are distributed, but the decision mechanism remains "off-line". In fact, the agents are controlled by a central manager agent located in the HHC and the route planning for the caregivers is generated "off-line". To the best of our knowledge, only Itabashi et al. [23] propose an "on-line" distributed support system for the home care scheduling problem using a multi-agent system. Clients and caregivers are equipped with PDAs and can communicate with the HHC support system. The latter has a database and contains three types of agents (interface agent, scheduler agent, and helper agent). A negotiation mechanism among agents, associated with clients and caregivers, is used to execute autonomously the care schedule. The patients and caregivers use PDAs to confirm the schedules established by the agents. However, care schedules are drawn up centrally at the home care center.

The main parameters of assignment and routing problems are the following: (1) the number of human resources involved; (2) the large number of assisted patients; and (3) the large number of care services provided to the patients and the temporal dependency between the care activities and the human resources. These parameters are static and allow us to

Table 1
Classification of the different papers reviewed.

	Off-line approaches	On-line approaches
OR	[2,3,4,9,6,10–17].	
MAS	[21,22].	[23]

OR: Operational Research approaches – MAS: Multi-Agent System approaches.

consider a large problem. Unfortunately, some approaches such as those based on MILP models are very expensive in computational time and become inefficient in taking real-world problems into account. In addition, unexpected events occur that introduce uncertainty and temporal issues associated with the need to react in real-time. Typically, traffic jams, road accidents, and any other traffic issues are common and should be taken into account when designing a real-world routing problem [5]. In a more general context, [24] states that the different problems addressed in the HHC literature do not take into account the uncertainty with regard to the duration of the care activity and/or the travel time. Moreover, in recent studies, [7,6,25] suggest that future studies should explore assignment and routing problems with uncertainties or disruptions. All these remarks are in line with the expectations of HHC managers who would like decision support systems that can solve assignment and routing problems in large real-world situations in reasonable time and produce valid solutions (i.e., feasible compared to the real situation) with numerous time constraints and in a dynamic context [6]. For this, some decisions must be made “on-line” in a distributed way.

In Table 1, the papers reviewed are classified according to the type of resolution (“off-line” or “on-line”). In the majority of related works, assignment and/or routing problems are solved “off-line” in a centralized manner. A central HHC manager is responsible for all decisions sent to caregivers with no “on-line” feedback.

To reduce the gap between existing studies and HHC managers’ expectations, we first define a global framework to structure the resolution of assignment and routing problems.

3. Global framework and architecture

3.1. Preliminary hypothesis relative to the context

Differences may be observed in the HHC system in different countries according to the “reasons for switching to the HHC system” and the “type of care provided” [7]. These differences impact the way in which the assignment and routing problems are solved. Yalçındağ et al. [26] investigated different methods to solve assignment, scheduling, and routing problems for HHC services according to their level of flexibility defined by their ability to explore a wider solution space. The methods that solve the sub-problems jointly in a single phase are the most flexible in terms of exploring a wider solution space. These methods are interesting for small instances. The methods guided only by assignment decisions are considered rigid and fail to provide feasible solutions. The authors conclude that the two-phase decomposition method that solves the sub-problems in two phases (phase 1: assignment and scheduling; phase 2: routing) provides good, efficient solutions for different problem sizes.

Based on the results presented in [26], solving assignment and routing problems individually but sequentially is consistent with practices in France, as well as other countries such as Quebec. First, the assignment sub-problem must be solved less frequently than the caregivers’ routes, i.e., the assignment problem needs to be solved only when patients are admitted or discharged, while caregivers’ routes must be solved more frequently (the patient’s care plan changes every day). Second, the objective function of the assignment sub-problem balances and improves the caregivers’ workload, whereas the objective function of the caregivers’ route is to find the shortest route. Third, caregiver route problems evolve in a dynamic, real-world context and the main difficulties are taking into account dependency constraints between caregivers, coping with random events such as traffic jams and road accidents, reacting quickly to unexpected disturbances, and making good decisions in reasonable time.

In this context, the global architecture of the HHC system must integrate both off-line and on-line modules that can deal with the two sub-problems sequentially (“assignment” and “routing”). The proposed global architecture is presented in the next section.

3.2. HHC system architecture

The proposed architecture is based on the ORCA control architecture presented in [27] and [28], where one of the basic principles was to design a global optimizer (in our case, the HHC level) that interacts with local reactive controllers (in our case, the caregivers). Thus, the problem was solved sequentially using the architecture presented in (Fig. 1). The upper module is an off-line centralized process that assigns patients to caregivers and defines the caregiver’s list of patients for each workday, as well as an “optimal” planned route. More precisely, the off-line centralized process makes two kinds of decisions: (1) assigns patients to caregivers according to several criteria such as the type of care provided, the patient’s preferences, and the location; and (2) draws up a “planned route”, defined by the shortest route for each caregiver, independently

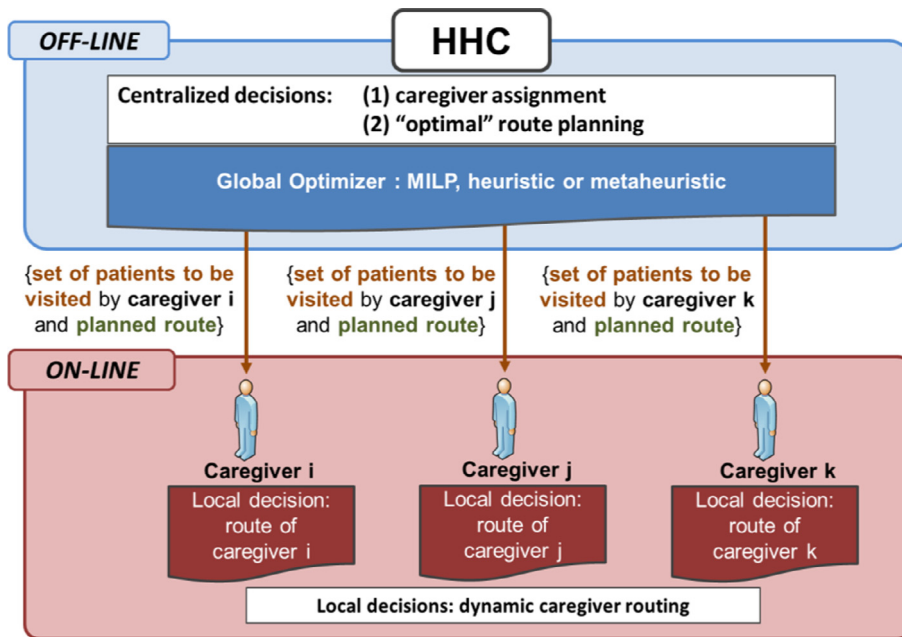


Fig. 1. HHC system architecture.

of the others. The planned route is then generated taking only the patient's and caregiver's locations into consideration, with no traffic problems. These two decisions can be made using classical OR tools, heuristics or metaheuristics.

The lower module concerns local decisions made on-line. According to Fig. 1, a set of patients to be visited and planned routes are generated daily by the off-line module. The planned route generated for each caregiver explicitly provides an order in which to visit the patients. Sets of patients and planned routes are considered as input data for this on-line module.

In the on-line module, each caregiver must dynamically solve his own routing problem to cope with numerous disturbances and unpredicted events (e.g., traffic jams). The chosen order of the patients to be visited can then be modified in a distributed way by applying local decision rules.

As presented previously, one of the limitations in existing studies concerns on-line decision-making in a dynamic context. The rest of this paper focuses on this "dynamic routing problem" and our contribution to solving this problem is presented in the following section.

4. Dynamic routing problem

In this section, the "dynamic routing problem" is described and the assumptions are presented. Caregiver behavior is then defined and the local on-line decision rules are detailed.

4.1. Dynamic routing problem assumptions

We consider a set of patients P $\{P\#1, P\#2, \dots, P\#n\}$ that require a list of care activities chosen from set A $\{A\#1, A\#2, \dots, A\#a\}$, provided by a set of caregivers C $\{C\#1, C\#2, \dots, C\#m\}$ with the following constraints:

For the patients and the care activities

- Each patient has his own location, i.e., home.
- The patients are passive and do not take initiatives during the routing decision process. The patients only inform the caregivers of their availability when asked.
- Each day, each patient from P is visited by several caregivers from C .
- For each patient in P , the list of daily care activities is known and is a subset of A .
- For each patient, no order was introduced to provide the care.
- The duration of each care activity in A is known.
- Patient's care activities cannot be performed at the same time or overlap.
- Only one caregiver from set C can perform each care activity in A . Therefore, there is no interchangeability among caregivers for care activities.

For the caregivers

- Each caregiver in set C obtains a list of patients and a planned route from the HHC on a daily basis, as explained in the previous section.
- Each caregiver only interacts with his own patients.
- The caregiver's route starts and finishes at the caregiver's home.
- The caregiver cannot return home before the route is finished.
- A caregiver can visit the same patient one or more times per day.
- A caregiver cannot perform more than one care task at the same time.
- If a caregiver arrives at a patient's home while the patient is unavailable, i.e., if the patient's current care task is not yet finished, then the caregiver waits until the patient is free.

4.2. Global caregiver behavior

The caregiver's behavior during the working day is represented by Petri nets in Fig. 2. The working day is divided into the following stages:

- (1) The caregiver begins his workday at home.
- (2) The caregiver receives a list of patients and a planned route from the HHC authority.
- (3) The caregiver decides which patient should be visited according to his local environment, e.g., list of patients who have not been visited yet, travel distances, patient availability. To help the caregiver make an efficient decision based on his degree of autonomy, different decision rules are defined and embedded in our system.

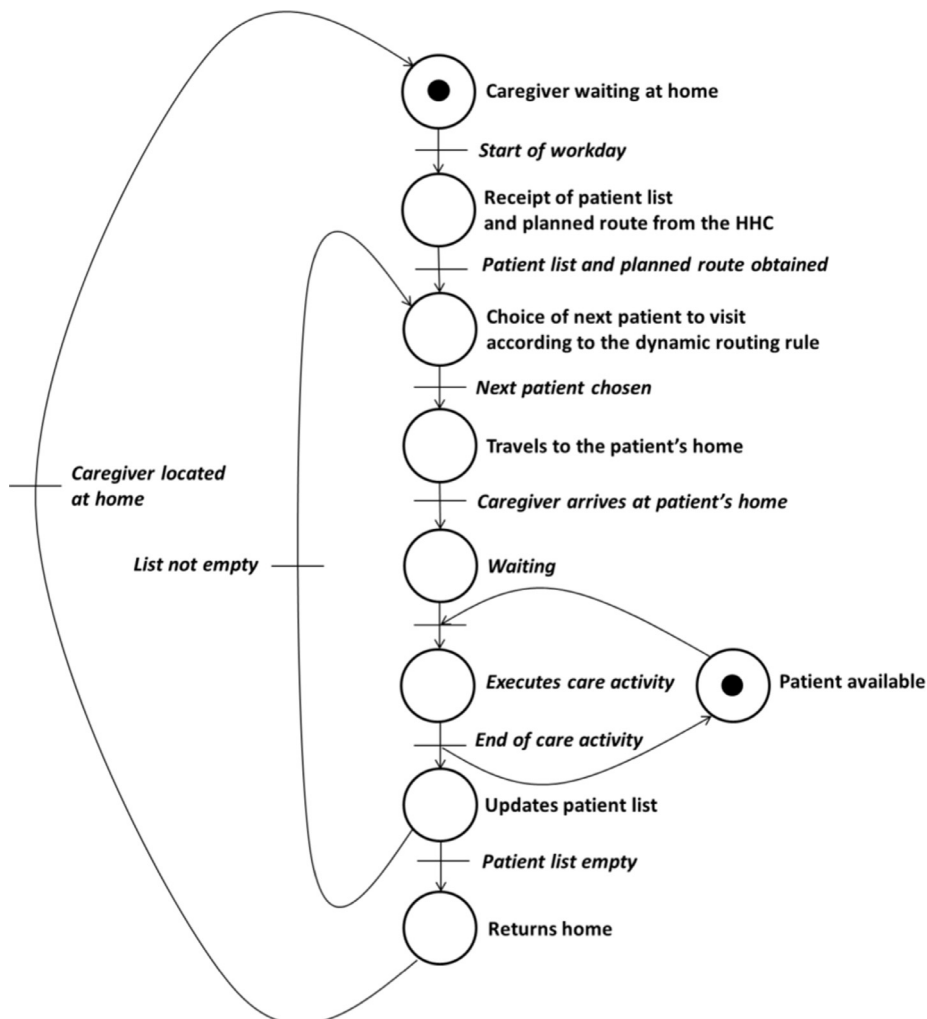


Fig. 2. Description of the caregiver's behavior.

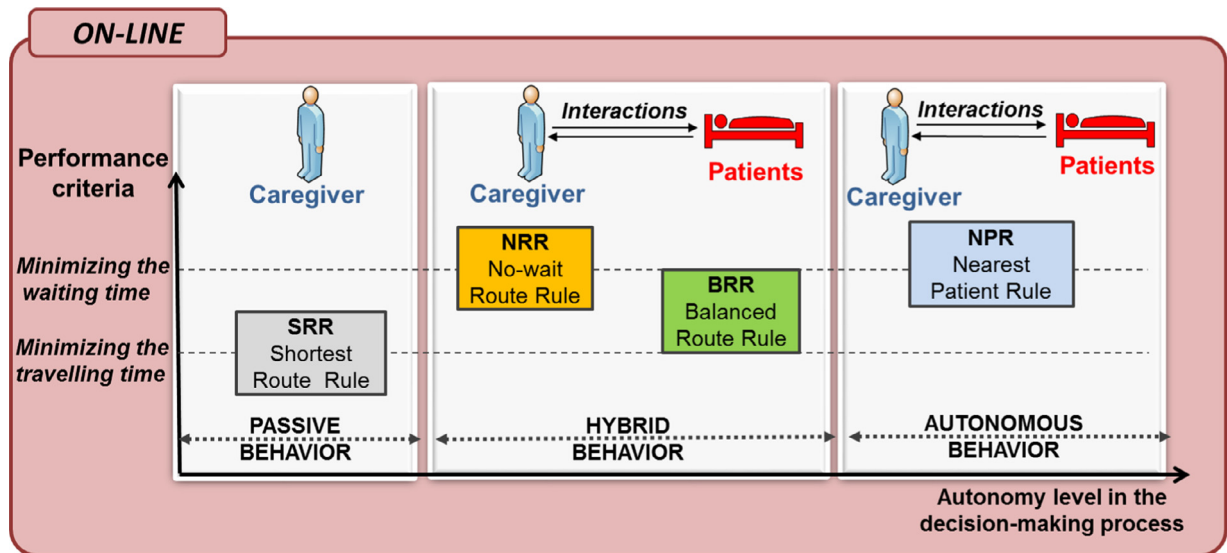


Fig. 3. Caregiver dynamic routing rules.

- (4) The caregiver goes to the chosen patient.
- (5) Upon arrival at the patient's home, if the patient is unavailable or otherwise occupied (i.e., the current care task is still ongoing), the caregiver must wait until the patient is available.
- (6) The caregiver can perform the required care task once the patient becomes available.
- (7) Once he has finished, the caregiver updates the patient list by removing the treated patient.
- (8) If the patient list is empty, the caregiver returns home. Otherwise, the process returns to Step 3.

The next part presents how the caregiver can make decisions using dynamic routing rules.

4.3. Dynamic routing rules

As depicted in Fig. 3, three main categories of caregiver behavior are considered:

- Passive behavior: the caregiver follows scrupulously the planned route provided by the HHC,
- Autonomous behavior: the caregiver autonomously calculates his own route and decides which patient to visit next without taking the planned route into account,
- Hybrid behavior: the caregiver adapts dynamically the planned route according to the context via interaction with the patients.

With respect to these categories, four decision rules are considered to help the caregiver plan his own route and choose his next patient.

Each decision rule attempts to optimize one of the following criteria:

- The caregiver's waiting time at each patient's home when the patient is unavailable,
- The time the caregiver spends on the road.

The three categories of caregiver behavior and related decision rules are detailed below according to the level of autonomy and the performance criteria considered.

4.3.1. Passive caregiver behavior: the Shortest Route Rule (SRR)

In this first category, by applying the **Shortest Route Rule (SRR)**, the caregiver scrupulously follows the planned route. Consequently, from a decisional point of view, the caregiver is passive and there is no interaction with the patients. Only the "travel time" is considered and the patient's availability is not taken into account.

4.3.2. Autonomous caregiver behavior: the Nearest Patient Rule (NPR)

This second category, the **Nearest Patient Rule (NPR)**, corresponds to "autonomous" caregiver behavior. The caregiver does not follow the planned route, but opportunistically selects the nearest patient available in a pure "on-line" reactive manner, minimizing the "waiting time" because the caregiver only considers the waiting time at the patient's home as unproductive. As depicted in Fig. 4, the caregiver scans the patient list to find the nearest patient. He calls this patient and

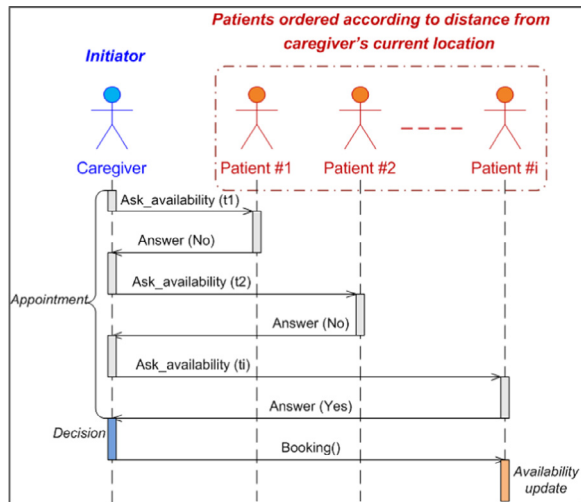


Fig. 4. Interaction for the Nearest Patient Rule.

asks if the patient will be available from the moment he arrives at the patient's home until the care task is completed. If the patient is available during this period, then this patient becomes the next destination. If the patient is unavailable, the caregiver continues his search on the list to find the next nearest patient, and calls him to check if he is available, and so on. Finally, if all the patients are unavailable, the caregiver has to travel to the nearest patient on the patient list and wait until that patient becomes available. Fig. 4 illustrates a case in which the *i*th patient is available.

4.3.3. Hybrid caregiver behavior

Two rules are defined regarding hybrid caregiver behavior:

- For the **No-wait Route Rule (NRR)**, the caregiver follows the planned route but can change his route if the patient is unavailable. This decision rule switches between the HHC goal (minimize the duration of travel) and the caregiver's goal (minimize the waiting time at the patient's home). As shown in Fig. 5, the caregiver calls the remaining patients on his ordered list of patients until he finds an available patient, i.e., the patient must be available from the moment the caregiver arrives at the patient's home until the care task is completed. Fig. 5 illustrates a case in which the 3rd patient is available.

If every patient is unavailable, the caregiver goes to the home of the first patient on the list and waits until the patient is free. By following this rule, the caregiver minimizes the waiting time at the patient's home.

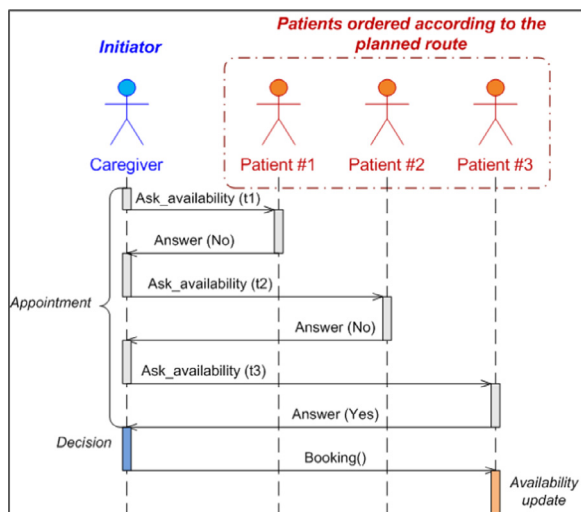


Fig. 5. Interaction for the No-wait Route Rule.

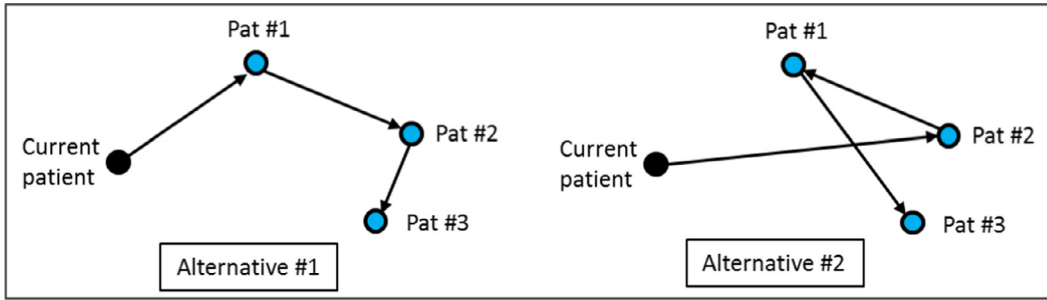


Fig. 6. Alternative routes for the Balanced Route Rule.

- The **Balanced Route Rule (BRR)** is also based on the “planned route”, but a quantitative assessment is performed to evaluate two alternative paths. The first minimizes the travel time and the second reduces the waiting time. This assessment provides the caregiver with a better visibility of the impact of his choice of itinerary.

The caregiver calls the first of the remaining patients on the list defined by the “planned route”, and asks if he is available from the moment he arrives at the patient’s home until he finishes the care task. If the patient is available during this period, then the patient becomes the next destination. Otherwise, the caregiver calls the second patient on the list:

- A. If the second patient is unavailable, then the first patient on the list becomes the next destination.
- B. If the second patient is available, the caregiver must deal with two alternatives:
 - o Follow the “planned route” and wait or
 - o Go to the second patient on the list and then return to the first patient.

The choice is made with the aim of minimizing the unproductive times by comparing the duration of the two alternatives:

1. The duration of the shortest path with waiting time (see Fig. 6, left-hand image) is the sum of the travel time from the current patient to Pat #1, the waiting time at Pat #1’s home, the travel time from Pat #1 to Pat #2, and the travel time from Pat #2 to Pat #3.
2. The duration of the other path with no waiting time (see Fig. 6, right-hand image) is the sum of the travel time from the current patient to Pat #2, the travel time from Pat #2 to Pat #1, and the travel time from Pat #1 to Pat #3.

The duration of the care activities is not considered because it is identical for both paths. With the BRR, the caregiver evaluates the duration of each alternative path and makes a decision taking into account the local context, i.e., the patient’s availability and duration of travel between patients. Fig. 7 illustrates a case in which patient #2 was available. Both alternatives were assessed and ultimately patient #1 was booked.

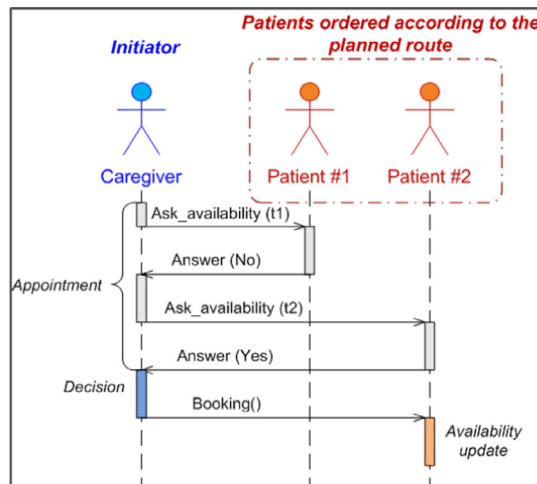


Fig. 7. Interaction for the Balanced Route Rule.

5. Implementation and simulation protocol

This section describes the simulation platform developed to test and evaluate the different dynamic routing rules. The objective was to evaluate the impact of the decision rule on caregiver performance and patient comfort.

5.1. Multi-agent simulation platform

The multi-agent paradigm is well-suited to implementing the dynamic aspect of the aforementioned rules and more particularly interactions among patients and caregivers. Two types of agents were defined in our model:

- **Patient agent:** These agents represent HHC patients. They are immobile, totally passive, and do not take initiatives during the decision process. They just inform the caregiver agents of their availability when asked.
- **Caregiver agent:** These agents represent the caregivers. They move around the HHC district and can perform care activities at the patient agents' location. Caregiver agents only interact with their own patients. An important characteristic is their degree of autonomy with regard to deciding which patient to choose next.

The multi-agent model was implemented using NetLogo (agent-based programming language). NetLogo is a free, open-source, multi-agent environment created in 1999 by Uri Wilensky at Northwestern University [29]. This simulation environment is widely used by researchers in the field of Agent-Based Modeling. We chose NetLogo for its functionalities allowing quick GUI development and for its ability to model distributed decision making. Railsback and Grimm [30] and Vidal [31] show how to study and simulate agents and their interactions in agent-based systems.

Fig. 8 illustrates the NetLogo interface developed for the simulator.

This simulation tool was applied to test and experiment the case studies presented in the next part.

5.2. Simulation experiment protocol

5.2.1. Input data

Five parameters were used in each case:

- Number of caregivers
- Number of patients
- Number of patients per caregiver
- Number of care activities per patient per day
- Duration of care

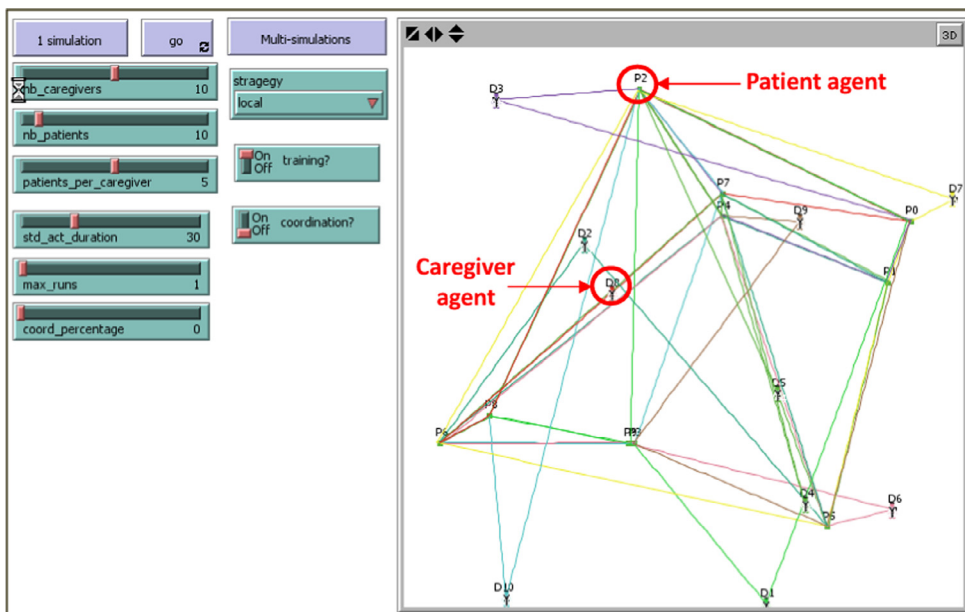


Fig. 8. Screen capture of the NetLogo interface. Example of a small case study.

The data related to the travel parameters was invariable and is presented by:

- Scene (zone covered)
- Mean caregiver speed

5.2.2. Performance indicators

Different performance indicators were considered for the caregivers and the patients.

Concerning caregivers, the importance was to reduce the travel times and the waiting times at the patient's home. Concerning patients, their quality of life was the main consideration and was defined by the waiting time between care activities.

5.2.2.1. *Caregiver performance indicators.* Three indicators were defined to evaluate the caregivers' routes:

Cmax: Cmax is the time elapsed between the moment the caregiver leaves his home to the moment he returns home after finishing all his care tasks,

Trav: The travel time is the sum of the times spent on the road during the working day,

Wait: The waiting time is the sum of the waiting times at each patient's home during the working day.

5.2.2.2. *Patient performance indicators.* Three indicators were used to evaluate patient comfort.

Begin: Begin corresponds to the moment when the first care activity starts at home,

End: End corresponds to the moment when the last care activity is completed,

P_wait: The waiting time is the time elapsed between the start of the first care activity and the end of the last care activity minus the duration of the said care activities.

5.2.3. Simulation protocol

For each case study, the simulation protocol involved three steps:

1. *Step #1:* The initial caregiver locations (i.e., home locations) were randomly generated and their coordinates remained unchanged during the different experiments.
2. *Step #2:* To test the most general situation and avoid an over-specific geographical distribution, 500 independent experiments were run. This number of experiments was chosen to ensure that the mean values were statistically significant. Each experiment corresponded to an HHC working day with the following considerations:
 - i. At the beginning of each experiment, the patients' locations were randomly generated.
 - ii. To avoid simulation bias of the sequential treatment of the parallel tasks in Netlogo, 100 replications of the simulations were run modifying only the order of the caregiver list.
 - iii. For each replication, the four decision rules were simulated using the data detailed below.
 - iv. At the end of the 100 replications, the best performances were retained for each rule.
3. *Step #3:* At the end of the 500 experiments (performed 100 times), averages of the different performance criteria (for caregivers and patients) were computed. As shown below in [Tables 2-4](#), the number of experiments was sufficient to ensure that the mean values were statistically significant. Indeed, the 95% Confidence Interval (CI) was lower than 3% ($p < 0.03$) of the average value for all the average indicators.

For each case study, simulations were carried out on a PC with an Intel core duo (T9600), 2.80 Ghz, 4 Gb RAM running XP professional. The computational times for each replication for case studies 1 and 2 were less than 0.01 s and 1 s, respectively.

5.2.4. Case studies

Two case studies inspired from classical types of HHC provider in France were considered:

- **"Case 1"** considers small size problems. This case study is relevant for many public HHC in France and corresponds to a tertiary hospital in many semi-rural areas. The data and the parameters used are presented in [Table 2](#) below.
- **"Case 2"** considers large size problems. The scale of this case study in terms of the number of caregivers and patients is representative of the second largest HHC in France, located in Lyon (the third largest town in France with more than 2 million people). The data and the parameters used are presented in [Table 4](#) below.

Table 2
Parameters for experiment#1: “Case 1”.

	Value
Number of caregivers	10
Number of patients	10
Number of patients per caregiver	5
Number of care activities per patient per day	[3,7]
Duration of care	30 min
Scene	100 km ²
Mean caregiver speed	60 km/h

Table 3
Assignment of patients to caregivers in “Case 1”.

	Caregiver Location	P#1	P#2	P#3	P#4	P#5	P#6	P#7	P#8	P#9	P#10
Caregiver#1	(42, 2)										
Caregiver#2	(24, 36)										
Caregiver#3	(10, 64)										
Caregiver#4	(32, 69)										
Caregiver#5	(72, 60)										
Caregiver#6	(30,9)										
Caregiver#7	(96,49)										
Caregiver#8	(18,19)										
Caregiver#9	(87,24)										
Caregiver#10	(55,58)										

Table 4
Parameters for experiment #2: “Case 2”.

	Value
Number of caregivers	130
Number of patients	300
Number of patients per caregiver	7
Number of care activities per patient per day	[3,4]
Duration of care	30 min + uniform (-10, 10)
Scene	100 km ²
Mean caregiver speed	60 km/h

5.2.4.1. *Experiment #1: “Case 1” input and parameters.* To assess the performances of the four decision rules, a high level of complexity was considered by introducing strong temporal dependencies among the caregivers. As every patient has between 3 and 7 visits per day, the caregivers’ routes are hugely interconnected.

The values of the parameters used are summarized in Table 2.

Table 3 details the assignment of patients to caregivers, depicted by gray cells. According to their pathology, patients may receive a variable number of care activities and be visited by several caregivers. For example, patient P#1 requires three visits per day provided by caregivers #2, #6, and #8, while patient P#2 has seven visits per day.

As previously introduced in Table 2, each caregiver provides care for 5 patients per day. The assignment “caregivers/patients” remained the same throughout the different experiments.

5.2.4.2. *Experiment #2: input and parameters of “Case 2”.* Experiment #2, which considered larger size problems, assessed the scalability of the proposed decision rules.

Table 4 shows the values of the parameters used in experiment #2.

In this case study, the number of caregivers and the number of patients per caregiver increased the complexity. Moreover, we introduced variability in the duration of care.

The assignment “caregivers/patients” was defined randomly and remained the same throughout the different experiments.

Table 5
Results for the caregivers' routes: "Case 1".

	NPR			NRR		
	<i>Cmax</i> ^a	<i>Trav</i> ^a	<i>Wait</i> ^a	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
Average	426.3 ± 2.2	253.3 ± 2.2	23 ± 0.6	437.6 ± 2.4	263.8 ± 2.3	23.8 ± 0.6
Min.	354.6	173.6	8.2	359.7	177	9.6
Max.	513	331.9	47.2	532.5	363.1	59.4
	SRR			BRR		
	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
Average	418.1 ± 2.1	224.5 ± 1.9	43.6 ± 1	414 ± 2	233.3 ± 1.9	30.7 ± 0.7
Min.	351.7	158	17.3	348.2	164.7	13.2
Max.	502.5	297.9	87.4	482.9	310.5	58.4

^a Expressed in minutes.

Table 6
Results for patients: "Case 1".

	NPR			NRR		
	<i>Begin</i> ^a	<i>End</i> ^a	<i>P_wait</i> ^a	<i>Begin</i>	<i>End</i>	<i>P_wait</i>
Average	40.6 ± 0.8	324.3 ± 1.7	133.8 ± 1.7	56.4 ± 1.1	365.8 ± 2.4	159.4 ± 2.2
Min.	19.2	267.4	81.6	29.1	294	99.1
Max.	77.2	386.2	183	116.3	469.9	248.5
	SRR			BRR		
	<i>Begin</i>	<i>End</i>	<i>P_wait</i>	<i>Begin</i>	<i>End</i>	<i>P_wait</i>
Average	74.9 ± 1.6	351.4 ± 2.3	126.5 ± 2.3	67.8 ± 1.4	343.6 ± 2.1	125.7 ± 2.2
Min.	29	278.6	43.7	28.1	282	53
Max.	157.5	431.8	200.3	128.3	418.2	195.5

^a Expressed in minutes.

Table 7
Results for caregivers' routes: "Case 2".

	NPR			NRR		
	<i>Cmax</i> ^a	<i>Trav</i> ^a	<i>Wait</i> ^a	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
Average	524.9 ± 0.5	300.8 ± 0.4	17.4 ± 0.2	519.1 ± 0.5	296.5 ± 0.5	15.9 ± 0.1
Min.	519.3	295.4	14.7	513.7	291.8	13.6
Max.	533.1	307.5	21.4	525.9	303.9	17.4
	SRR			BRR		
	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
Average	501.6 ± 0.3	261.7 ± 0.3	33.3 ± 0.3	500.1 ± 0.3	269.0 ± 0.2	24.5 ± 0.2
Min.	497.8	254.7	29.4	497.4	266.2	22.6
Max.	505.2	269.2	36.9	503.5	271.3	26.7

^a Expressed in minutes.

6. Simulation results

The objective of this first round of experiments (i.e., experiment #1 and experiment #2) was to highlight the efficiency of the proposed decision rules defined by the ability of the latter to minimize the caregiver's travel time and waiting time at the patient's home.

6.1. Simulation results

6.1.1. Simulation results of experiment #1: "Case 1"

In the following tables, the best value for each indicator is highlighted in bold.

Caregiver performance: Table 5 presents the caregivers' results for the four decision rules.

Patient performance: Table 6 presents the patients' results for the four decision rules.

6.1.2. Simulation results of experiment #2: "Case 2"

The results for caregivers and patients are presented in Tables 7 and 8, respectively.

Table 8
Results for patients: “Case 2”.

	NPR			NRR		
	<i>Begin</i> ^a	<i>End</i> ^a	<i>P_wait</i> ^a	<i>Begin</i>	<i>End</i>	<i>P_wait</i>
Average	87.8 ± 0.2	364.9 ± 0.4	187.5 ± 0.5	109.4 ± 0.2	407.6 ± 0.5	208.6 ± 0.5
Min.	85.6	360.1	182.3	107.0	402.9	203.1
Max.	90.4	370.7	193.6	111.3	415.5	217.4
	SRR			BRR		
	<i>Begin</i>	<i>End</i>	<i>P_wait</i>	<i>Begin</i>	<i>End</i>	<i>P_wait</i>
Average	116.0 ± 0.1	390.9 ± 0.2	185.3 ± 0.2	113.6 ± 0.1	387.5 ± 0.2	184.4 ± 0.2
Min.	114.5	387.7	182.9	112.4	384.8	181.5
Max.	117.5	393.9	187.3	114.8	390.4	187.3

^a Expressed in minutes.

6.2. Results analysis and discussion

6.2.1. Comparison of the caregiver's route

Tables 5 and 7 present the behavior of the four decision rules. Whatever the situation for the caregiver, SRR always favors the shortest route, and consequently travel times are the shortest. However, as SRR does not check patient availability, caregivers often wait at patients' homes when the patient is unavailable, and so their waiting time is the highest.

NPR and NRR mainly help reduce the caregiver's waiting time at the patient's home, so the waiting time is lower but the travel time is higher than with the other two rules.

Even if NPR and NRR pursue the same main goal, their performances with regard to travel time are different according to the context. NPR (cf. Table 5) is better at minimizing the caregiver's travel time than NRR for a high level of temporal dependency. Conversely, NRR is better at minimizing the caregiver's travel time than NPR (cf. Table 7) for a low level of temporal dependency. This can be explained by the fact that NRR follows the planned route if its patients are available, so if the temporal dependency is low, the risk of patients being unavailable is also low. In the case of high temporal dependency, the caregiver follows a chaotic route defined by the availability of its patients, whereas NPR tries to go to the nearest available patient whatever the temporal dependency.

Regarding “travel time”, it can be noted that in Tables 5 and 7 SRR is always better than NPR. In other words, a centralized approach based on the shortest travel duration is better than a reactive distributed local decision strategy based on the nearest patient. However, in practice, SRR is difficult to implement in HHC because the caregivers do not like to wait at the patient's home as the time is generally considered as unproductive, whereas the travel time is not. According to our experience, NPR is widely used by caregivers in HHC.

Regarding *Cmax*, Tables 5 and 7 show that BRR provides the best results. These results highlight the fact that the best decision consists in evaluating the performance of the centralized method (i.e., the planned route) with an alternative local decision. Although the decision is based on the hypothesis that the next patient visited will be available in the future, this method is good enough to make the right decision.

6.2.2. Comparison of patient treatment duration

In Tables 6 and 8, the behavior of the four decision rules is analyzed in terms of start and end of treatment each day and waiting times between consecutive treatments. NPR achieves the best *Begin*. This result was expected because each caregiver chooses to visit his nearest available patient at the start of the route. NRR has the second best *Begin* because the caregiver's goal is to avoid waiting at the patient's home. Therefore, at the start of the workday, each caregiver visits a different patient. SRR achieves the worst *Begin* because caregivers follow the planned route and sometimes the first patient is the same on several caregivers' lists. Thus, some patients wait for their caregivers because their caregiver is waiting at another patient's home.

In Table 9, we present a comparison of the four decision rules with regard to patient treatment duration.

The duration of treatment is defined as the time elapsed between the start of the first care task and the end of the last task. SRR and BRR provide the best performances and are quite close, while NPR and NRR are the worst. This result is due to the fact that NPR and NRR avoid any waiting at the patient's home and go to a patient available, so the patient often has to wait between two care activities. For SRR, the caregiver follows the planned route and often waits at a patient's home, which reduces the patient's waiting time between care activities.

Finally, let us compare the daily duration of treatment obtained by the four decision rules with theoretical daily treatment durations. As we mentioned previously, the number of care activities for the patients in case study “Case 1” was between 3 and 7. The “theoretical value” was, therefore, defined as the sum of its care activities. We calculated average theoretical treatment durations from the average number of care activities per patient, that is to say, 5 care activities performed at a patient's home, i.e., 150 min or 2.5 h. On average, the treatment duration for each patient in “Case 1” ranged between 275.7 and 309.4 min, i.e., 4.5 and 5.2 h.

Table 9

Average treatment duration per patient per day for case studies "Case 1" and "Case 2".

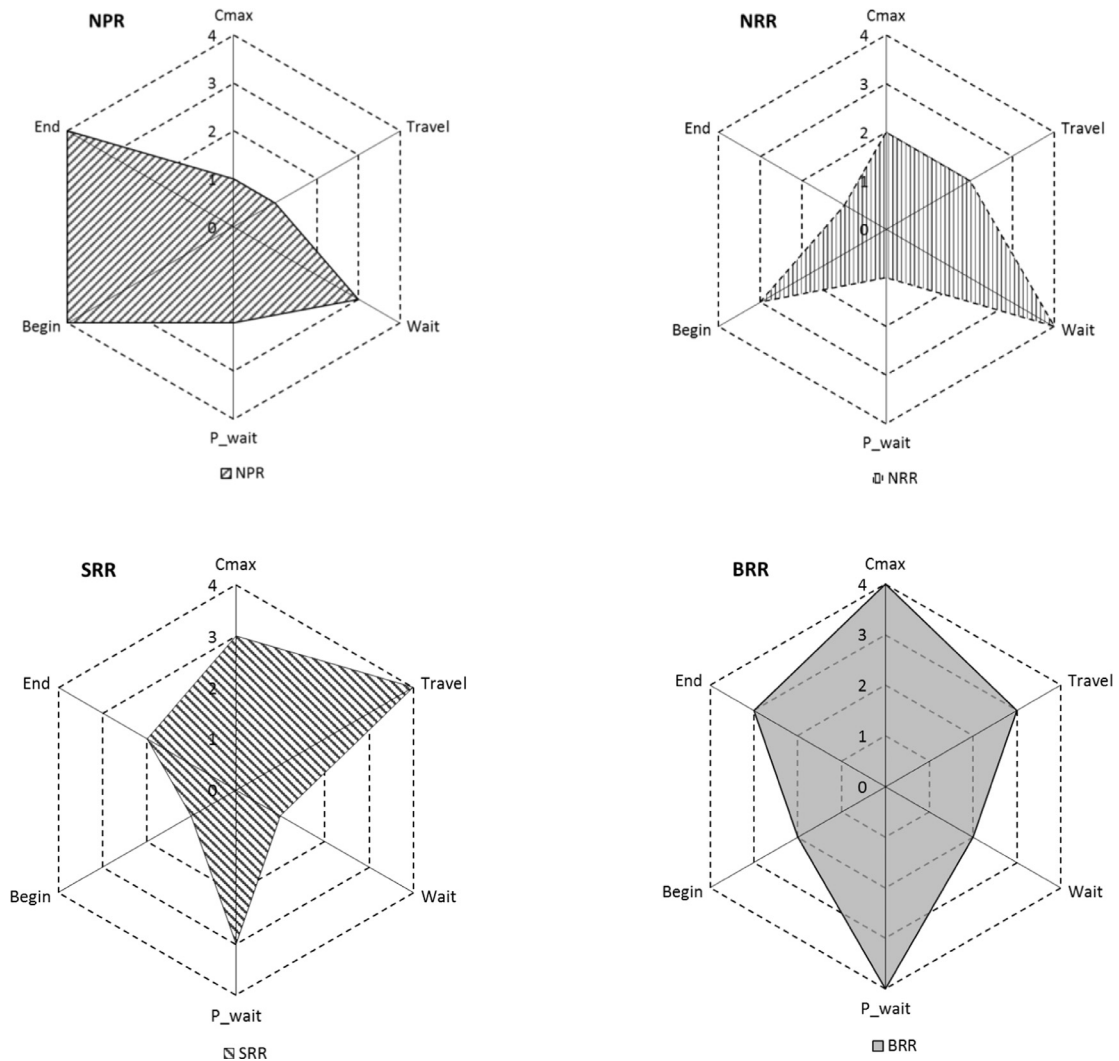
	Theoretical value	NPR	NRR	SRR	BRR
<i>"Case 1"</i>					
Avg. patient treatment duration	150.0	283.8	309.4	276.5	275.7
Min. patient treatment duration	90.0	231.6	249.1	193.7	203.0
Max. patient treatment duration	220.0	333.0	398.5	350.3	345.5
<i>"Case 2"</i>					
Avg. patient treatment duration	91.0	277.1	298.2	274.9	274.0
Min. patient treatment duration	90.0	274.5	295.9	273.2	272.4
Max. patient treatment duration	120.0	280.3	304.2	276.4	275.7

All the values are expressed in minutes.

The average waiting time was closer to the care duration for NPR, SRR, and BRR, and greater for NRR. Table 9 shows that for "Case 2", this phenomenon is more significant for patients with three or four treatments; their waiting time was always over 3 h.

This poor result was expected since all the decision rules are caregiver-oriented. In other words, the caregiver makes a decision in order to minimize the amount of time he wastes. These decisions always have an impact on patient waiting time.

For a global comparison, the efficiency of the decision rules is summarized in Fig. 9. For each performance indicator, the four decision rules are ranked. The decision rule that achieves the best performance obtains a score of 4 and the one with

**Fig. 9.** Spider graph of the decision rule performances.

the worst performance is valued at 1. So, according to the spider graph, the greater the surface area the more efficient the decision rule.

As shown in Fig. 9, when the caregivers design their own routes by choosing the nearest patient available, they spend a lot of time traveling but they minimize their waiting time at the patient's home. Among the four decision rules, NPR is the most efficient for the patients' performance indicators. If the caregivers strictly follow the planned route, i.e., SRR, their travel time is reduced but their waiting time is hugely increased. In this situation, to reduce the waiting time, the caregivers can take the initiative of modifying their planned route using the NRR rule and only respecting the planned route if the patients are available. Simulations show that this new route is always worse than SRR but gives the best results in terms of caregivers waiting time.

In conclusion, the trade-off between "off-line" centralized and "on-line" distributed decision rules, i.e., BRR, provides better solutions than pure centralized (SRR) or distributed (NRR) rules in terms of caregiver's travel and waiting times. However, the only limitation of BRR is linked to the assessment of the two choices, which requires the two alternative paths to be calculated but with a very short computational time, around 1 s per replication in the worse cases.

Finally, when the caregivers applied BRR and chose the best alternative between waiting at the patient's home and visiting an available patient on their list, the simulations showed that BRR was the best approach.

7. Relevance of the distributed approach

In this section, we discuss the improvement obtained with the proposed distributed approaches according to the following properties:

- **Pertinence:** the proposed approach must exhibit performances close to the best approaches or close to a theoretical lower bound.
- **Scalability:** the approach must be relevant whatever the size of the HHC. When the size or the complexity of the problem increases, the computational time for solving the problem must increase linearly.
- **Robustness:** whatever the context, the approach must be able to cope with disruptions (e.g., variations in travel time or duration of care).
- **Implementability:** the proposed approach should be easily implementable on mobile devices (on a smartphone for example).

7.1. Pertinence

We defined several lower bounds to assess the pertinence of the four decision rules to design the caregiver's route:

- **For travel duration:** The first theoretical lower bound is the duration of the caregiver's shortest route when the temporal dependency constraints are relaxed. For each caregiver, the duration of the shortest route is calculated by enumeration of all possible tours because caregivers have very few patients to visit each day, i.e., 5 or 7. The SRR decision rule forces the caregiver to follow the shortest route, so we define the average *Trav* obtained by this rule as the theoretical lower bound for the travel duration (e.g., 224.5 ± 1.9 min for "Case 1").
- **For waiting times:** the NPR or NRR decision rules prevent waiting at the patient's home, so their average *Wait* could be considered as the lower bound for the waiting time (e.g., 23 ± 0.6 min for "Case 1").

We thus considered the sum of the two previous lower bounds (travel duration and waiting time) as a relevant theoretical lower bound.

Tables 10 and 11 show the differences between the performances of the four decision rules and the theoretical lower bounds for "Case 1" and "Case 2", respectively.

In Table 10, the difference between the theoretical lower bound and the four decision rules is between 6.7% and 16.2% for the 500 independent experiments.

The results for "Case 2" in Table 11 confirm those obtained for "Case 1" and are even better; the difference is between 3% and 8%. The better results obtained for "Case 2" can be explained by the level of complexity of both cases. The number of care activities per patient per day considered in "Case 1" ([3,7]) is greater than in "Case 2" ([3,4]). Consequently, the temporal dependency, which causes many disruptions, is higher in "Case 1" and thus explains the lower performance.

In conclusion, whatever the case studied, this distributed approach provides good, pertinent solutions in terms of minimizing the caregiver's route.

Table 10
Differences between the performances of the rules and the theoretical lower bound for "Case 1".

	Average lower bound (minutes)	Gap (%) NPR	Gap (%) NRR	Gap (%) SRR	Gap (%) BRR
Travel duration	224.5	12.8%	17.5%	0.0%	3.9%
Waiting time	23	0.0%	3.7%	89.7%	33.5%
Travel duration + Waiting time	247.5	11.6%	16.2%	8.3%	6.7%

Table 11
Differences between the performances of the rules and the theoretical lower bound for “Case 2”.

	Average lower bound (minutes)	Gap (%) NPR	Gap (%) NRR	Gap (%) SRR	Gap (%) BRR
Travel duration	261.7	15.0%	13.3%	0.0%	2.8%
Waiting time	15.9	9.0%	0.0%	109%	54%
Travel Duration + Waiting time	277.6	8.0%	6.0%	3.0%	3.0%

Table 12
Results for the caregivers' routes subjected to disruptions affecting travel duration.

	NPR			NRR		
	<i>Cmax</i> ^a	<i>Trav</i> ^a	<i>Wait</i> ^a	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
No disruption	415.8 ± 10	241.7 ± 8	24.1 ± 7	439.4 ± 13	258.5 ± 10	31.3 ± 8
Disruptive rate = 10%	424.6 ± 12	246.7 ± 10	27.9 ± 7	443.0 ± 14	260.3 ± 12	32.7 ± 9
Disruptive rate = 20%	425.0 ± 13	247.1 ± 10	28.4 ± 8	448.2 ± 17	263.9 ± 14	34.4 ± 10
Disruptive rate = 50%	439.9 ± 22	258.1 ± 16	31.8 ± 10	460.5 ± 22	273.6 ± 15	36.9 ± 12
				SRR		
				BRR		
	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>	<i>Cmax</i>	<i>Trav</i>	<i>Wait</i>
No disruption	414.7 ± 8	209.9 ± 0	54.8 ± 8	405.9 ± 6	218.7 ± 5	37.2 ± 9
Disruptive rate = 10%	415.3 ± 10	211.7 ± 3	53.6 ± 9	406.2 ± 8	219.3 ± 5	36.9 ± 9
Disruptive rate = 20%	418.3 ± 11	212.9 ± 5	55.4 ± 10	408.9 ± 9	221.1 ± 7	36.8 ± 10
Disruptive rate = 50%	424.7 ± 14	218.4 ± 7	56.4 ± 12	414.3 ± 13	228.1 ± 9	36.2 ± 10

^a Expressed in minutes.

7.2. Scalability

In [16], two centralized models based on a multi-TSP coordinated approach and an RCPSP approach were developed and tested. Both mathematical models were formulated as Mixed Integer linear Programming models and implemented using LINGO 11.0 solver (LINDO System Inc.). For a case study including 10 caregivers and 10 patients, with 5 patients per caregiver, the computational time to obtain a good solution was around 2.5 h and for an optimal solution was over 6.5 h.

In our distributed approach, the solution for one experiment, i.e., 100 replications for “Case 1”, was obtained in about 1 s. Moreover, for a medium case study, i.e., around 50 patients and 10 caregivers, both models developed in [16] did not find a feasible solution even after running for several hours, while our approach found a solution within 1 s per replication for our largest case study “Case 2”.

The two cases studied show that the size of the problem or the level of complexity has a low impact on the computational time for the simulation of the decision rules. Moreover, as mentioned above, when the scale of the problem changes, and particularly when the number of patients increases, the quality of the caregiver's route is maintained.

7.3. Robustness

A third experiment was defined to assess the robustness of the decision rules in the presence of disruptions affecting the caregivers' travel time.

7.3.1. Experiment #3: impact of disruptions on “Case 1”

These tests were only carried out on the smallest case study (“Case 1”) because, as mentioned previously, this case study introduces strong temporal dependencies among caregivers and thus the greatest amount of potential conflict between caregivers' routes.

In this experiment, the caregivers' travel times were altered by disruptions due to the weather, traffic jams, or other disruptive factors. Disruptions were randomly generated during the simulation when a caregiver decided to go to the next patient's home. The travel duration was modified by multiplying the initial travel duration by a randomly generated ratio ranging from 0.5 to 1.5. In this way, the travel duration could be shorter or longer than the travel duration used to design the shortest route.

Several tests were performed for different levels of disruption corresponding to the different disruptive rates and the results are summarized in Table 12.

Table 12 displays the average values and the standard deviation of the duration of the caregiver's route with no disruptions, and when the travel duration was randomly modified by 10%, 20%, and 50%. The results show that the disruptive rate has a very low impact on *Cmax*. This is due to two factors: (1) the decision rules used by caregivers are local decisions, and (2) the disruptions are randomly modified.

7.4. Implementability

The implementability is strongly dependent on the complexity of the calculations to be performed. As highlighted by the different sequence diagrams for each decision rule, very few computations were necessary regarding the different people involved (caregivers and patients). As shown in [21,23,32,33,34], recent computing and communication devices such as smartphones and tablet PCs can easily support the interaction between caregivers and patients.

8. Conclusion and prospects

This paper addresses the operational-level HHC management problem in a dynamic context with numerous constraints, uncertainties, and random events. In the literature, two sub-problems have been identified: assignment of patients to caregivers and design of caregivers' routes. A global framework has been proposed to solve the two sub-problems separately in a sequential manner. The first "off-line" decision, i.e., assignment of patients to caregivers, was beyond the scope of this paper and will be addressed in another paper. The second "on-line" decision, i.e., the caregivers' routing problem, was solved to define the caregiver's route. The aim of this paper was to solve the routing problem in a dynamic context using an MAS-based approach. For this, we developed and tested four decision rules to help caregivers make good decisions according to their level of autonomy and the local context. The performance of these decision rules was assessed on a multi-agent platform. An experimental study was proposed based on two case studies ("Case 1" and "Case 2") that represent HHC services of different size. The discussion highlights and compares the performances of each decision rule according to five properties: efficiency, pertinence, scalability, robustness, and implementability. Finally, we concluded that the BRR rule, which is a trade-off between an "off-line" centralized approach and an "on-line" distributed approach, is better than the three others at minimizing the caregivers' travel time, with or without disruptions. However, the four selection rules were not effective in minimizing the patient's waiting period because our approach was caregiver-oriented. Finally, we demonstrated the pertinence, scalability, robustness, and implementability of our distributed approach.

In this paper, our study focused on a dynamic routing problem in HHC, but some future lines of research can be outlined:

- Disruptions to travel times due to the weather and traffic jams were considered to test the robustness of the global architecture, but new experiments could be performed to investigate other types of disruptions such as adding or removing patients during the workday or an imposed order of patient care.
- With the current approach, the decision rules only promote communication between caregivers and their own patients. An alternative approach could be to promote communication between caregivers to design their route and to compare both approaches in terms of travel time, waiting time, and time lost in communication.
- Finally, another issue will be to develop a "patient-centered" approach allowing patients to play an active role in the decision process by managing their own schedules. This novel approach can be compared to the caregiver-oriented architecture presented in this paper.

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