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Abstract. Home health care centers face many variations during the execution of routes, compromising initial solution planning. Several studies propose robust solutions to counter small variations, but very few are interested in resilient solutions to counter disruptions. In this paper, we propose a collaborative resilient approach based on real-time re-optimization of caregivers' routes by considering environmental data at the time the disruption comes out (remaining visits, current position of caregivers, etc.). We analyze and compare this new approach with two others from the literature using discrete event simulation. Our approach reduces the total delay time in most scenarios (by 50% to 90% in the best cases) and outperforms literature approaches in half of the cases. These primary results show that there are many avenues for improvement, such as the development of a better solver or a heuristic and the hybridization between different resilient approaches.

1 Introduction

Aging population and increasing life expectancy, as we can see in France and in other developed countries, leads to an increase in the number of people with loss of autonomy and in dangers caused by fragility. Some statistics illustrate the seriousness of these situations: the life expectancy in France has now reached the age of 85.6 years old for women and 79.7 years old for men [1]. This increase in life expectancy accelerates the aging of the population in France, as we can now affirm that in 2050, about a third of the French population will be over 60 years old, according to the study of National Institute of Statistics and Economic Studies (INSEE)[1]. This demographic change is

[1] https://www.insee.fr/fr/statistiques/1375921?sommaire=1375935

associated with an increase in elderly fragility and a rise in chronic diseases such as diabetes, heart failure that require long-term monitoring and care management.

Under this global context, hospitals have found themselves unable to meet care demands. In order to relieve their congestion, new strategic directions are observed. One of these directions is related to the transfer of some patients' care activities from hospitals to their homes. As such, we are currently observing a rapid growth in Home Health Care (HHC) organizations.

HHC organizations are facing management difficulties in terms of coordination and continuity of care, as it has been outlined in several research works [2–4]. These issues are induced by the HHC organizations' characteristics (limited budget and resources) and the specific HHC processes which are totally different from classical hospitalization processes. Indeed, HHC processes require the coordination and cooperation of caregivers both in time and space according to their skills and profiles [5]. For satisfying the care demands, we have to organize caregivers to carry out the required care visits while managing the exchange of necessary information among the different stakeholders involved in HHC processes. Whenever uncertain events occur (e.g., vehicle breakdown, last-minute cancellation of requested care services, etc.), the collaboration between the caregivers when performing their assigned HHC services is required.

In France, HHC is mainly managed by regional associations which coordinate the activity of all the involved staff (caregivers). To ensure good coordination and cooperation in the operational field, the HHC coordinator who is usually a nurse employed by the HHC organization, is mandated to guarantee the development and ongoing maintenance of HHC service by performing a three-stage cycle process:

- Initial planning construction: this phase deals with determining a short-term (daily or weekly) assignment of caregivers to HHC services according to patients' requests, and then generating caregivers' work rounds with the consideration of many specific constraints.
- Care visit monitoring: this phase consists in the monitoring of the realization of HHC visits scheduled in the previous phase. It aims to identify possible risks in the execution of requested care visits, by analyzing the daily transmitted information from the caregivers about the timeliness of the HHC acts and the evolution of the patient's health conditions.
- Planning adjustment: In this phase, the HHC coordinator needs to adjust several initial plannings to accommodate the various issues detected in the previous phase, and the uncertainties taking place during the route of caregivers. As mentioned before, the cooperation between caregivers is sometimes required, to avoid the delay of visits and even missed scheduled events. It would result in a reduction of patients' satisfaction and even delay the best time to treat the patients.

In this work, the emphasis is placed on the third stage: planning adjustment. We propose a resilient approach based on real-time re-optimization of routes when a disruption arises, to ensure the satisfaction of the patient's time windows as much as possible. We analyze and compare this approach with two others from the literature, using discrete event simulation.

The remainder of this paper is structured as follows. In section 2, a literature review related to our study is presented and we highlight the originality of our investigation. Section 3 provides a description of the use case, the simulation model, the mathematical model for the solver, and the design of experiments. Finally, Section 5 provides the results, and some research perspectives are presented in Section 6.

2 Literature Review

The problem of designing the routes of the caregivers is known in the literature as the Home Health Care Routing and Scheduling Problem (HHCRSP). As a very topical subject, it generates a lot of research that has been reviewed in [4] and [6].

Similarly to other routing problems, real-world HHCRSP are submitted to various uncertainties and the execution of the planned routes is often disrupted. As a result, recent studies tend to include such uncertainties within the developed models. The variability in the duration of the services or the travel times is widely studied and is often handled with stochastic models [7,8]. Shi et al. [9] prefer using a robust model that they solve with different metaheuristics (variable neighborhood search, tabu search, and simulated annealing). Stochastic and robust models enable the decision-maker to anticipate uncertainties in order to keep the planned routes with only minor changes. For example, Carello and Lanzarone [10] use a robust model to build a good solution that remains feasible as long as there is a reduced number of patients whose service time is longer than expected.

These solutions are generally not acceptable whenever a more significant disruption happens. Then, dynamic strategies are preferred even though they can be very costly. Cancellations from patients, acceptance of new requests, or absence of caregivers are typically the types of decisions that may require a dynamic approach. Yuan and Jiang [11] develop a tabu search to deal with such unexpected events. Their objective is to minimize the deviations from the initial plan. Du et al. [12] propose a memetic algorithm with a local search to include new emergent patients in the routes while minimizing response time.

There are different levels of dynamism, based on the emergency of the disruption, and their frequency. Pillac et al. [13] categorize two types of approaches for dynamic routing problems. The first option is periodic re-optimization: the optimization of a static problem is periodically conducted at fixed times and takes into account the changes that have occurred since the last optimization [14]. The main advantage of the approach is in the use of algorithms developed for static problems but it is not suited to deal with urgent requests. On the contrary, continuous optimization updates the solution whenever the data changes [15].

In order to repair the routes after a disruption, cooperation between the agents may be necessary. The cooperation can be centralized: the decision-maker, or coordinator, is aware of the real-time situation and is also able to communicate with the agents during the execution of the schedule. In [16], the coordinator can call additional nurses to step in and perform services or re-route the nurses closest to the disturbed route.

Horizontal collaboration can also occur in decentralized approaches like multi-agent systems for example. Alves et. al [17] study the impact of vehicle breaks on the execution of the routes. They compare the results when the agents are passive (no change in the planned routes) or when they adopt an autonomous behaviour and undertake the services of the "broken" route. In [18], the integration of new patients into the routes is addressed with a multi-agent system with a negotiation protocol.

In this article, we study a realistic HHCRSP subject to variable travel and service times, but also major disruptions. We compare the effectiveness of agent collaboration in a centralized approach based on a re-optimization of the schedules with a decentralized simulation approach based on autonomous caregiver behaviours.

3 Methods

3.1 General Methodology and Use Case

This research work is the sequel of [19], where three different resilient approaches used to tackle disruptions during HHCRSP routes are analyzed and compared:

- Approach A (or "0" in [19]), the non-collaborative baseline called, consists of returning to the health center when the round is over to do administrative tasks without worrying about colleagues;
- Approach B (or "1"), a collaborative decentralized approach modelling the existing solution today, consists of helping colleagues when they have finished their rounds by calling them one by one to find out if they need help. The study of this approach is part of another research paper [19];
- Approach C (or "2") consists of centralizing information (on an application available on a smartphone, for example) to improve local decision-making. When a caregiver has finished his route, he consults the application to find out directly if a colleague needs help. This approach outperforms the previous two, enabling better collaboration between caregivers.

We propose here a new approach (D) which consists in re-optimizing the routes in real time using a solver, enabling collaboration as early as possible, and we compare it to the baseline (A) and the information centralization approach (C) using discrete event simulation.

The study case used for comparison is the same as in [19]:

- There are five caregivers performing five routes that start at 7 a.m. from the health care center, and end between 12 p.m. and 1 p.m. at the same location;
- Travel times are often short (usually less than five minutes) and are triangularly distributed more or less 30% around the average value;
- There are 140 care visits to perform, which are requested by 140 patients (one visit per patient), that are generally five minutes, but can sometimes last 10 minutes. They are both subject to variations (such as travel times, with the same distribution) and to disruptions: a care visit disrupted lasts one hour longer than expected.

- Time windows (i.e., time slot during which the caregiver must begin the care visit) last one hour for each visit;

The location of the (fictitious) patients is presented in Figure 1 on the left, and the routes of the initial solution schedule are on the right.

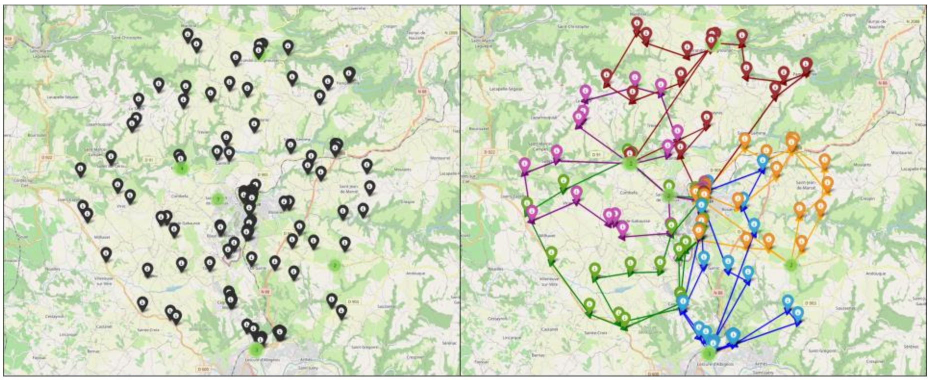

Fig. 1. Location of the patients and initial routes.

3.2 Simulation Model

To simulate the routes and assess the different approaches, we use a simulation model that is the same as used in [19] and represented in Figure 2: (1) the five caregivers are created and they retrieve their attributes and information for the next visit; (2) if they have finished their route, they go back to the station (approach A) or they help their colleagues (approach C); if not (3), the travel time to the next patient is calculated; (4) if the caregiver arrives late (i.e. after the time window), the total number of late arrivals is incremented: and (5) the care visit is carried out before they move on to the next patient. With approach C, when the caregivers have finished their route, they check if a colleague needs help (i.e. has encountered a disruptive event and is propagating his delay on the rest of his route). If so (6), the colleague wanting to help will take care of the next visit closest to him.

The performance indicators of the model are: (i) the total number of late arrivals and the cumulative late arrival time, and (ii) the end time of each route (knowing that a caregiver must finish before 1 p.m.).

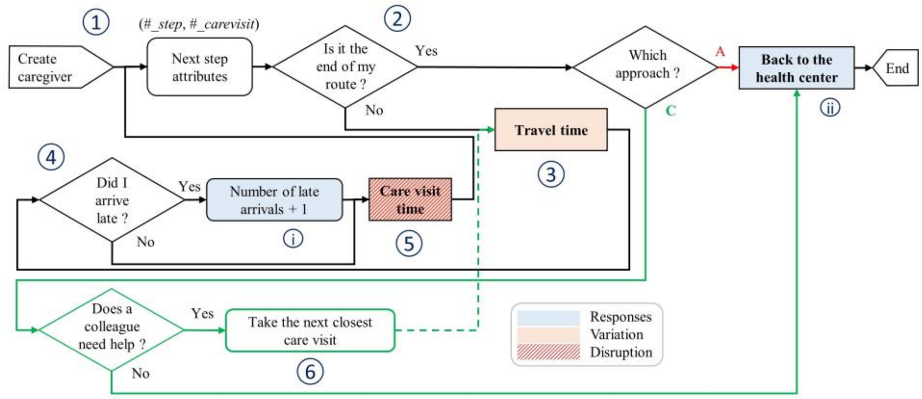

Fig. 2. Representation of the simulation model and the resilient approaches A and C

3.3 Mixed-Integer Linear Programming

Approach D, a resilient approach that we propose in this paper, consists of reoptimizing the home health care routes when a caregiver's route is disturbed, so that colleagues can help as soon as possible.

For example, a caregiver informs the health care center that his patient has died and he will therefore be immobilized for one hour longer than planned (time to call a doctor to certify the death, to call the family, the funeral, etc.). The health care center will then use a solver to reoptimize the routes considering the following environmental data (collected by a smartphone application for each caregiver for example):

- Only the remaining visits;
- The time of availability of each caregiver;
- The position of each caregiver when they will be available.

Figure 3 illustrates the links between the data, the simulator and the solver.

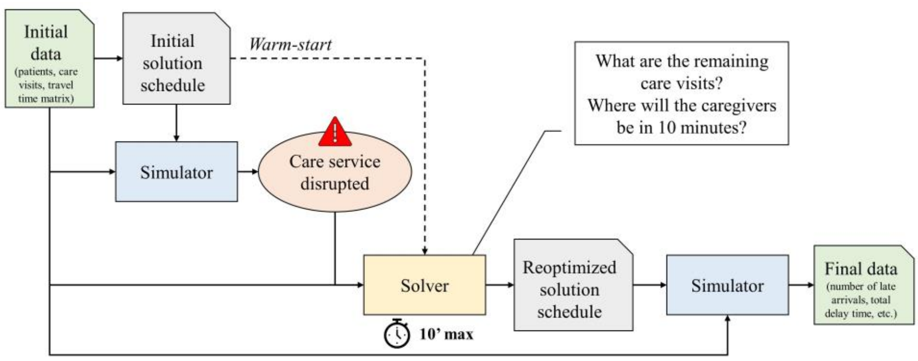

Fig. 3. Links between the data, the simulator, and the solver (approach D)

In the mathematical model, V is the set of remaining visits to be reoptimized and C is the set of caregivers. $X_{i,j,k}$ and $Y_{i,k}$ are binary decision variables that equal 1 if care visit i is made by k for $Y_{i,k}$ and if care visit j follows care visit i on route k for $X_{i,j,k}$. S_i is the time at which visit i begins, TW_i^- and TW_i^+ are the lower and upper bounds of its time window and DT_i is the delay time if the caregiver arrives late. AT_k is the time at which a caregiver is available (the time that he finishes the care visit he is performing when launching the solver) and P_k is his position (for the caregivers to leave where they are after re-optimization). Finally, $TT_{i,j}$ is the travel time to go from patient i to patient j, VT_i is the visit time of care visit i and M is a large constant.

The objective function is to minimize the total delay time, regardless of the number of late arrivals or the travel time. It is represented by equation (1).

$$min \sum_{i \in V} DT_i \quad (1)$$

The constraints of the mathematical model are the following:

$$\sum_{k \in C} Y_{i,k} = 1 \qquad \forall\, i \in V \quad (2)$$

$$\sum_{j \neq i \in V} X_{i,j,k} = Y_{i,k} \qquad \forall\, i \in V,\ \forall\, k \in C \quad (3)$$

$$\sum_{i \neq j \in V} X_{i,j,k} = Y_{j,k} \qquad \forall\, j \in V,\ \forall\, k \in C \quad (4)$$

$$S_i \geq TW_i^- \qquad \forall\, i \in V \quad (5)$$

$$S_i \geq \sum_{k \in C} (AT_k + TT_{P_k,i}) \times Y_{i,k} \qquad \forall\, i \in V \quad (6)$$

$$S_i + VT_i + TT_{i,j} - S_j \geq M \times \left(1 - \sum_{k \in C} X_{i,j,k}\right) \qquad \forall\, i,j \in V, i \neq j \quad (7)$$

$$DT_i = max\ (0, S_i - TW_i^+) \qquad \forall\, i \in V \quad (8)$$

$$Y_{i,k} \in \{0,1\} \qquad \forall\, i \in V, \forall\, k \in C \quad (9)$$

$$X_{i,j,k} \in \{0,1\} \qquad \forall\, i,j \in V, \forall\, k \in C \quad (10)$$

(2) guarantees that each care visit belongs to a single route. (3) and (4) assure that each care visit assigned to a caregiver has a predecessor and a successor. (5) and (6) ensures that a care visit does not start before its time window TW_i^- and before the assigned caregiver is available. (7) guarantees that two visits on the same route take place one after the other respecting the visit times VT_i and the travel times $TT_{i,j}$. (8) is the calculation of the delay time DT_i for each care visit, this is not its true form since it is linearized.

The solving time is a crucial parameter for the solver: it is a compromise between a very short resolution time allowing to quickly have a solution (potentially not efficient) that will redispatch all the next visits of the disturbed route, and a long solving time allowing to have a very efficient or even optimal solution but which will compromise the next visits of the disturbed route (because the time windows will be expired at the end of the solving time). Thus, after several attempts, it was decided to set a maximum resolution time of ten minutes.

Finally, to reduce unnecessary computation time, the initial solution schedule is given to the solver as a warm-start. Therefore, three results are possible at the end of the ten minutes:

1) The solver failed to find better than the initial schedule, and then returns it as the solution;
2) The solver succeeded in improving the initial solution;
3) The solver has found the optimal solution.

The mathematical model was coded in *python* using the library *Pulp* and the solver *CPLEX*.

3.4 Design of Experiments

In order to obtain significant results, 50 replications per scenario are carried out. A scenario corresponds to the execution of the home health care routes of the case study where the visit of a given patient is disrupted. The name of a scenario then corresponds to the number of the patient whose visit was disrupted.

For approach D, since each replication lasts ten minutes (corresponding to the solving time of the solver, the simulation time is almost instantaneous), then each simulated scenario lasts 50 x 10 = 500 minutes, or 8 hours and 20 minutes. Simulating all 140 possible scenarios would then take more than a month, which is why it was decided to simulate only a dozen representative scenarios (each scenario selected increments the number of remaining visits by ten, increasing the difficulty of finding the optimal solution for the solver). Simulated scenarios are presented in Table 1, where data comes from the initial schedule, which is deterministic, and therefore varies from one replication to another.

Table 1. The different simulated scenarios, with the Time of Arrival at the patient (ToA), the total number of visits remaining to be reoptimized (Num-reopt), and the number of visits remaining on the disrupted round (Num-disrupt).

Scenario	ToA	Num-reopt	Num-disrupt	Scenario	ToA	Num-reopt	Num-disrupt
P32	7:02	135	26	P30	9:56	62	11
P7	7:22	125	24	P137	10:19	50	12
P100	7:41	117	23	P78	10:38	42	10
P122	8:08	107	22	P40	10:59	31	8
P118	8:32	97	20	P125	11:25	20	4
P35	9:09	84	18	P12	11:41	12	2
P109	9:31	73	12				

4 Results

The total delay time (i.e. the objective function to minimize) is presented for each scenario in Figure 4.

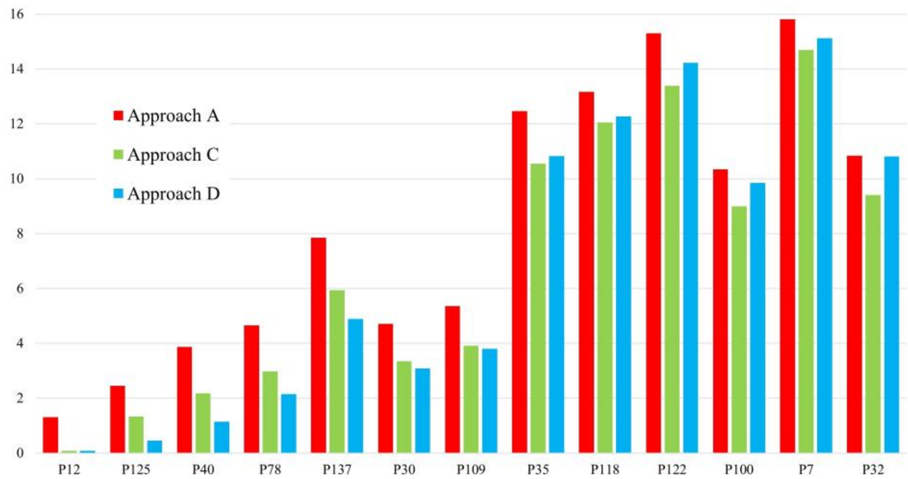

Fig. 4. Total delay time (in hours) for each scenario ($\sum_{i \in V} DT_i$).

First, approach A in red (the baseline where there is neither cooperation between the caregivers nor re-optimization of the routes after a disruption) has always the worse results.

Then, approach D in blue outperforms the two others in half of the cases, until scenario P35 where approach C in green is better. The more care visits to reoptimize, the more difficult it is for the solver to find a good solution in ten minutes. Consequently, the warm-start solution emerges as the best solution found and this is why the results are identical between approaches A and D for the P32 scenario where there are 135 care visits to consider.

To better compare the two approaches with each other, Figure 5 presents the reduction in the total delay time of the two approaches compared to the baseline for each scenario.

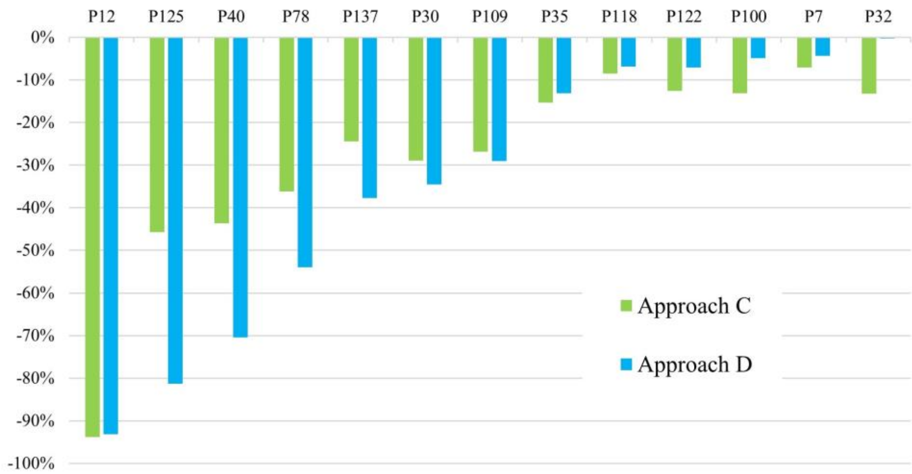

Fig. 5. Reduction in total delay time for approaches C and D compared to approach A.

Approaches C and D reduce the total delay time by 94% and 93% respectively for the P12 scenario, going from almost 80 minutes of total delay time to just five. Then, the reduction obtained with approach C falls to 46% and 44% while that with approach D only falls to 81% and 70%.

Towards the last scenarios, where there are still a hundred visits to be reoptimized, approach D no longer becomes effective and the reduction drops drastically to 5% for P100 and 0% for P32 while approach C allows a reduction of 13% for these same scenarios.

Finally, the second performance indicator is the end time of the routes: their distributions are represented in Figure 6.

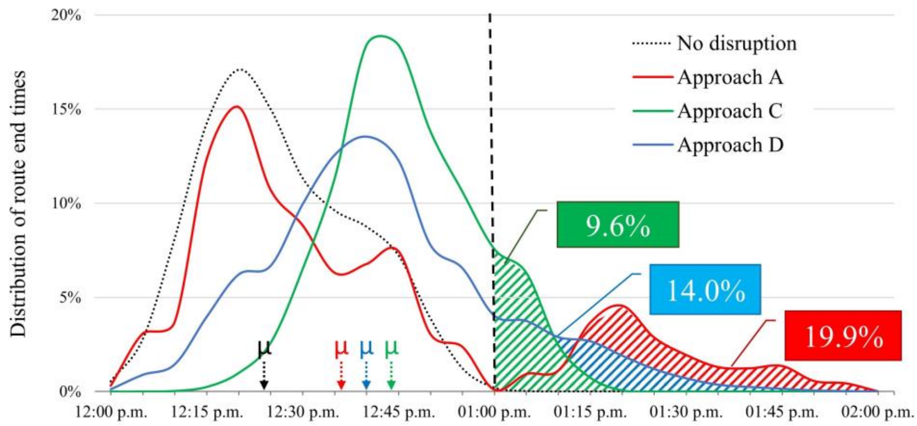

Fig. 6. Distribution of route end times and percentage of routes ending after 1 p.m.

The dotted black curve represents the distribution of route end times when there is no disruption: all the routes end before 1 p.m. and the average end time is 12:24 p.m. For approach A in red, approximately 20% of the routes exceed the target end time (this is the disrupted route among the five) and the average end time is 12:36 p.m.

For approach C, the number of rounds exceeding 1 p.m. is reduced by 52% but the average end time is at 12:44 p.m. while with approach D, the number of rounds ending after the target time is reduced by 30 % and the average end time is 12:40.

The choice of one of the two resilient solutions is therefore also a compromise between a low average end time and the number of rounds ending after the target time of 1 p.m.

5 Conclusion and Openings

In this paper, we propose a resilient approach based on real-time re-optimization of care visits to tackle disruptions arising during HHCRSP routes. We analyze and compare this approach with two others from the literature, including a decentralized approach based on autonomous caregiver behaviours, using discrete event simulation.

This new approach drastically reduces the total delay time when the number of visits to be re-optimized does not exceed eighty, because the collaboration between the caregivers is done as soon as possible. Beyond this limit number, the solving time is too short for the solver to find an interesting solution and it then becomes more interesting to switch to a decentralized approach.

Many avenues of research are now open to improve resilient approaches:

- The use of a better solver, heuristic or meta-heuristic;
- The hybridization between several resilient approaches (C and D for example), in particular according to the number of remaining care visits;
- Successive re-optimization during the execution of the schedule;
- Stop planning and only do execution using continuous re-optimization on each care visit made.

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