



A Hybrid Approach to Solve the Vehicle Routing Problem with Time Windows and Synchronized Visits In-Home Health Care

Jalel Euch^{1,2} · Salah Zidi¹ · Lamri Laouamer¹

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Abstract

With technological progress in particular telemedicine and health care, the information should meet and serve as well the needs of people and in particular whom with reduced mobility, the elderly as well as people with difficulties to access to medical resources and services. These services should be achieved in a fast and reliable manner based on case priorities. One of the major challenges in health care is the routing and scheduling problem to meet people's needs. Of course, the objective is to considerably minimize costs while respecting priorities according to cases that will face. Through this article, we propose a new technique for home healthcare routing and scheduling problem purely based on an artificial intelligence technique to optimize the offered services within a distributed environment. The automatic learning and search method seem to be interesting to optimize the allocation of visits to beneficiaries. The proposed approach has several advantages in terms of especially cost, efforts, and gaining time. A comparative study was carried out to evaluate the effectiveness of the planned technique compared to previous work.

Keywords Healthcare · Visit scheduling · Caregivers routing · Ant colony system · Synchronized visits · Clustering algorithm

1 Introduction

In the past 20 years, the number of beds in hospitals and private clinics has shortened. The aged population has led to a rise in the number of people with chronic degenerative diseases that give an increase to functional disabilities and handicaps. Patients who are undergoing treatment for advanced chronic diseases or palliative care want care that removes them as little as possible from their family environment for personal comfort reasons. Also, in the presence of pandemics which require the moving of patients at home as

in SAR-COV-19 (e.g., [1–3]). Besides, shuttling operations do not necessitate care that mobilizes a high-level technical platform and therefore heavy support at the hospital. It is for these reasons that in recent years, a comprehensive care structure has been developed outside walls of the hospital. Among these structures, the Establishments of Hospitalization at Home (EHH) is the best example.

The health system suffers from multiple economic and organizational problems. These problems have contributed to the emergence of multiple alternatives against traditional hospitalization. EHH was created as alternatives to possibly reducing healthcare system expenses while ensuring service quality satisfaction. The development of these structures is accelerating significantly, while the organization method followed remains artisanal and heterogeneous. The service provided by EHH is not limited to the provision of the care service, that is, the production and administration of medical and paramedical acts. Indeed, the service provider also includes a part of the operations management of the structure (organizational component).

Home hospitalization (HH) structures are growing around the world. They are considered as fully fledged healthcare establishments and assume all their obligations in terms of

✉ Jalel Euch
Jalel.Euch@fsegs.rnu.tn; J.Eleuchi@qu.edu.sa
Salah Zidi
salah_zidi@yahoo.fr
Lamri Laouamer
lamri_laouamer@yahoo.fr

¹ Department of Management Information Systems and Production Management, College of Business and Economics, Qassim University, Buraydah, Saudi Arabia

² OLID Laboratory, ISGIS, LR19ES21, Sfax University, 3021 Sfax, Tunisia



safety, quality, continuity of care, and respect for patients' rights. EHH is a complex and difficult system to manage from a human and material point of view. As a result, the structures of the EHH must be perfectly organized to ensure the quality, permanence, and continuity of care for patients, and to respect the workload of the careers, while reducing the costs relating to the processes care. We are interested in the design of caregiver tours for patients [vehicle routing problem (VRP)] taking into account multiple constraints (time windows, synchronization).

The problems of synchronization in VRP constitute a field of investigation which is still little explored but clearly identified. Synchronization is grouped into characteristics which create interdependence between routes. In a world where transport is increasingly multi-modal, interconnected, and where information systems allow increased flexibility to achieve more performance, there is no doubt that new route problems with synchronization will continue to appear. In this context, the exploration of the research space and the verification of time constraints offer quite interesting research subjects, at the crossroads between route optimization and scheduling.

In recent scientific literature, researchers discuss the organization of care in a hospital. Existing work deals with scheduling and routing problems for homecare vehicles. Currently, different health institutions in the world are authorized to provide home healthcare (HHC) services mostly in the presence of the COVID-19. Despite the rise of these institutions, the literature review shows that, to date, no research has been carried out to characterize the logistical challenges and requirements faced by HHC service administrators. These facts demonstrate the need to characterize and identify logistics management in the provision of HHC services, to contribute in reducing the gap between the state of the art and the reality of service provision in that context.

Thus, the contribution in this paper is to present a diagnosis of the logistics management of the institutions enabled by the routing and scheduling of caregivers to provide HHC services. The characteristics of VRP used are time windows, single structure, and synchronized visits, which means vehicles can return to the same patients, use a single warehouse, and consist of finding several caregivers' routes using a clustering algorithm. To improve the homecare service, the main objective is to minimize the total time necessary for caregivers to visit all patients, based on the best approach proposed. The obtained results will then be improved using the metaheuristic ant colony system (ACS) method which will provide a minimum total completion time.

To meet the stated objective, the paper is organized as follows: Sect. 2 presents a review of the literature, which identifies the state of the art regarding logistics management in HHC systems, and the existing research gap is evident. Section 3 describes and defines HHRSP. Section 4 presents

the details of the research methodology based on the ACS with clustering algorithm (ACS-CA). Section 5 presents the analysis and discussion of the results by identifying the opportunities to improve the home healthcare systems. Finally, in Sect. 6 we conclude.

2 Literature Review

This section makes a detailed exposition of the state of the art of those key concepts in which this research is framed, such as home healthcare routing and scheduling problems with synchronized visits and time constraints, metaheuristic and exact techniques. Within HHRSP, special attention is paid to those families of problems that present spatial/temporal restrictions, such as the family of problems of the traveling salesman problem (TSP) and VRP as these problems are particularizations or generalizations of the main problem tackled in this investigation planning problem of homecare assistants. Finally, a detailed description is made of the distribution algorithms metaheuristic and its application to different types of HHRSP problems.

Several types of VRP exist which has been studied in the literature. The VRP with time windows (VRPTW) where the vehicle must arrive at the customer in the definite time window. VRPTW's extensions contain additional features such as multiple trips (e.g., [4, 5]), multi-depots, and vehicle synchronization. A trip in this situation comprises a series of services before coming back to the warehouse.

Since the beginning of the 1990s, several studies have contributed to improve the logistics of transport in hospitalization to home, either in terms of cost efficiency or the optimization of journeys made by vehicles to bring nurses and technicians. VRP is an integer scheduling and combinatorial optimization problem that seeks the best way to visit and supply several customers with a specific fleet of vehicles. As proposed by [6], the VRP has great relevance in the fields of transport, distribution, and logistics. This problem consists in designing a set of deliveries or a collection of routes such that each route starts and ends in a deposit of the material to be distributed (e.g., [7–11]).

So far, many variations of the problem have been studied; for example, the vehicle fleet can be heterogeneous, and vehicles can collect or deliver on the same route; some vehicles may be disabled to visit some points; some clients require multiple visits within a time window; there may be several deposits; and deliveries can be divided between different vehicles (e.g., [12, 13]). Figure 1 represents the relationship between HHRSP and other different elements related to the problem.

The home healthcare planning problems have attracted recently the interest of numerous researchers, an interest that has been reproduced in the cumulative number of current



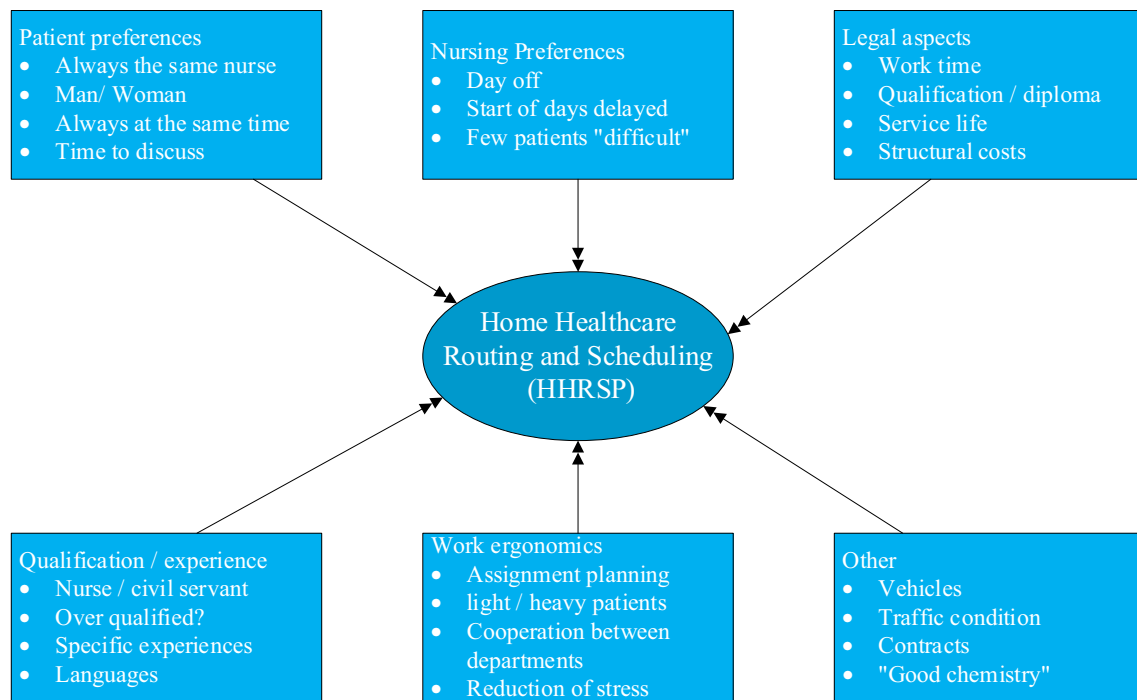


Fig. 1 HHRSP representation

publications as Fikar and Hirsch [14] and Cissé et al. [15]. This growing interest is motivated by two fundamental reasons, such as the progressive aging of our population and the need to provide health or assistance services in the place of residence of our elders. This type of service aims to meet the needs of our elderly in their place of residence, needs that may include health tasks, home care, preventive actions (physical therapy, occupational therapy), personal care or domestic care, among others, being this type of assistance, domiciliary, which is preferred by most of our elders. From an economic point of view, in Europe between 1 and 5% of the healthcare budget is used for this type of services (Source: World Health organization [16]); in other countries such as the USA, the number of people who received this type of assistance is amounted to 9 million in 2014, with a total of more than 67,000 providers and with an estimated cost between 210,000 and 317,000 million dollars (e.g., [17]). Among the different challenges facing companies that provide this type of service, a need is essential to provide efficient solutions that are capable of satisfying the growing demand, maintaining the satisfaction of customers and employees themselves, being viable under the economical point of view.

The companies that provide this type of service must make decisions in different areas, each of which corresponds to different combinatorial optimization problems, such as scheduling, staffing, and route planning for such staff point out that said decisions are made within three decision levels,

such as the strategic, tactical, and operational levels. In the strategic level, the decisions to be completed are related to how to partition the territory in which these types of establishments offer services, creating a cluster of patients in different areas. In the tactical level, the objective of the establishments that offer this type of service and the set of resources necessary to provide the appropriate level of service in each area must be identified. These resources can be human or material. To end, at the operational level, we determine which assistant will visit each patient.

In most cases, a set of homecare assistants, whose professional qualifications vary, including nurses, occupational therapy specialists, and personnel to carry out tasks at home or personal care, have to be assigned to a set of patients that require a heterogeneous set of services, each patient being in their place of residence, it being common for each assistant to visit different patients throughout their working day. From the above description, it can be deduced that there will be a set of restrictions that will allow deciding which assistant can be assigned to each patient, taking into account the qualification of the assistant and the type of service required by the patient. However, in reality, the problems and restrictions that providers of this type of service face are usually much more complex. For example, the applicable labor legislation must be taken into account, fairness when preparing the schedules of its workers, availability, which may include different types of contracts, vacations, attendance at training sessions, low disease, among others. Also, patients require



that the service is provided at certain times, this type of restriction is known as a time window, and its definition is identical to that provided in those sections. Finally, there is a whole set of restrictions associated with the displacement that each assistant must carry out between the different visits to each patient. First of all, it should be noted that there may be different means of transport such as the attendees' vehicle, public transport, bicycle, on foot, or a combination of the previous. Despite the challenges of decision making at different levels and the various constraints that must be met, most companies continue to plan their personnel manually.

In Kergosien et al. [18], this variant of HHRSP is formulated as a version of the TSP, specifically as a variation of the trade m -vendor problem with time windows. For this, the authors propose a series of additional restrictions and provide an exact formulation that can be solved by solving a mixed integer programming (MIP) problem. There is a popular of academics who have formulated the problem as a sweeping statement of the VRP in which a set of restrictions specific to the problem have been added. However, the studies that address the HHRSP differ from the VRP in that they present certain characteristics that hinder their solution and that must be considered:

- Continuity in the provision of tasks: These types of restrictions ensure that each patient is assigned to a small set of homecare aides with synchronized visits.
- Temporal dependency and compatibility between tasks: For example, one task must be performed immediately afterward or two tasks cannot be performed at the same time.
- Characteristics of patients and assistants: Each assistant can have a set of characteristics or skills which must be taken into account when being assigned to a patient. Similarly, each patient can have a set of preferences that limit the set of attendees who can visit them.

The different solution methodologies applied to HHRSP resolution are classified in different ways depending on the selected criteria. Considering the planning horizon, one can distinguish methods that focus on solving problems 1 day (single period) or those that are focused on solving several days, even months (multiple periods).

One of the first works that addressed this subfamily of problems from the optimization point of view was proposed by Begur et al. [19] in which the solution of this variant is combined within a decision support system for a firm in the USA; it must be noted that this technique did not take on consideration the time window constraints, and its objective was to minimize the total travel time, as well as the workload between the diverse nurses. Framed within a system to help the decision making is the work

carried out by Bertels and Fahle [20], in which exact and non-exact techniques are combined (hybrid). The cases used are considered for a single day, within 20–50 nurses, and by 111–326 patients.

Bredström and Rönnqvist [21] emphasize the significance and difficulty of including temporal constraints of synchronization and precedence in this family of problems. Specifically, the authors experiment with instances of problems in which the simultaneous presence of several assistants is required, such as lifting people with reduced mobility or tasks in which an assistant is required to visit a patient after another assistant has visited. The authors provide a MIP formulation, with a hybrid approach.

Rasmussen et al. [22] propose a dynamic column generation included within a Branch-and-Price scheme to solve an HHRSP with temporary dependencies, which affect the start of tasks. The authors formulate the HHRSP by considering five categories of precedence restrictions. In Liu et al. [23], an algorithm based on Branch and Price to solve an HHRSP of a Chinese company is presented, highlighting the need to include lunch breaks on each of the routes generated for each attendee. The authors use the CPLEX Software solver and two types of instances. The first is an adaptation of the instances proposed by [24], while the second comes from a set of real data provided by a Chinese company. Akjiratikarl et al. [25] propose a particle swarm optimization to plan a group of homecare caregivers in the UK; in total, more than 100 daily tasks are planned for a total of 50 patients and must be assigned to 12 homecare assistants, providing savings of up to 31% about the total distance traveled. In Trautsamwieser and Hirsch [26], the authors propose a Branch-and-Cut and Branch-and-Price algorithm to solve an HHRSP in which patients must be visited throughout the week, within a time window requiring the visit of homecare assistants with certain skills and characteristics. The total number of hours that each assistant can work is limited, both daily and weekly. Also, certain breaks must be made throughout the workday. Likewise using a full formulation, Cappanera and Scutellà [27] solve a weekly HHRSP, where the use of patterns takes on special interest when generating the planning of each attendee. These patterns, which are initially generated, have a double objective; in the first place, they ensure the continuity of the service, and on the other, they guarantee the compatibility between assistants and tasks. Afifi et al. [28] give decision support based on simulated annealing to launch daily homecare scheduling with synchronization. A hybrid iterated local search (ILS) with a variable neighborhood descent (VND) to solve the VRPTW with different visits is offered in En-nahli et al. [29]. Table 1 summarizes a classification of works done for the HHRSP in terms of characteristics constraints.



Table 1 Classification of works in terms of characteristics constraints

References	Constraints					Methodology
	Time windows	Synchroni- zation visits	Patient prefer- ence	Precedence	Disjunction	
Liu et al. [35]	✓			✓		Tabu search (TS), genetic algorithm (GA)
Duque et al. [36]	✓		✓			A flexible two-stage solution strategy
Yuan and Fügenschuh [37]	✓		✓			Heuristic algorithm
Misir et al. [38]	✓			✓		Hyper-heuristics
Rest and Hirsch [39]	✓		✓			MIP and tabu search
Afifi et al. [28]	✓	✓	✓			Set of local improvement methods
Ait Haddadene et al. [40]	✓	✓		✓		GRASP+ILS
En-nahli et al. [29]	✓	✓				Local search
Braekers et al. [41]	✓		✓			A large neighborhood search heuristic
Shi et al. [42]	✓	✓	✓			Fuzzy chance-constraint model
Du et al. [43]	✓		✓	✓		MIP+Genetic algorithm with local search
Frifita et al. [44]	✓	✓				General VNS
Decerle et al. [34]	✓	✓		✓		Memetic algorithm
Issabakhsh et al. [45]	✓	✓	✓			MIP
Demirbilek et al. [46]				✓		Cheapest insertion heuristic
Liu et al. [47]	✓	✓				An adaptive large neighborhood search
Euchi [1–3]	✓	✓				General ant colony
Our study	✓	✓				Ant colony system with clustering algorithm (ACS-CA)

3 The VRPTW with Synchronization Visits In-Home Health Care: Problem Definition

We consider a list of patients needing and a set of care services. Each care service is categorized by a period of care, and many resources are required to perform the care, a skill required such as the earliest start date and the latest service start date. Human resources work complete-time categorized by a qualification assorting from 1 to 5. The nursing staff begins and ends their tour in the EHH structure and must not exceed a maximum workload during the day. He must allocate care to patients and have a meal break while respecting the time windows. The waiting time for a resource is the time that elapses between the date of arrival of the resource at the patient's home and the date of the earliest start of care.

The problem is described as a VRP problem with time windows with synchronization of visits. Given a set of patients, a set of caregivers, and a homecare system (HCS), the goal is to find a path for each caregiver, starting and ending at the HCS and visiting a given set of patients. Several caregivers, depending on their availability, can take care of each patient. Patient visits must be synchronized, that is, care is provided at the same time by two caregivers.

Ultimately, the HHRSP consists of designing a set of routes over a planning horizon, in such a way that the homecare service is provided for each patient while minimizing

or maximizing a certain interest metric and respecting the different existing restrictions.

The problem to be solved in the HHRSP can be presented in this manner:

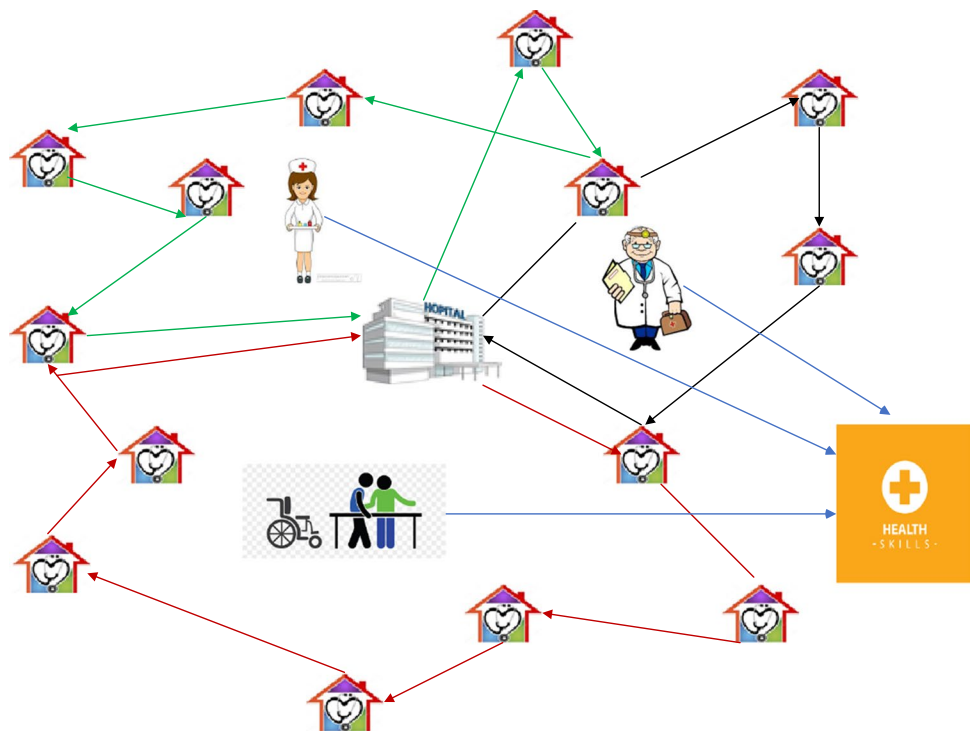
Given: A list of patients dispersed within a geographic zone and a list of caregivers.

Task: The set of visits that each attendee must carry out should be determined, trying to minimize some previously specified metrics, such as the full traveled distance or the waiting time of each client. Specifically, it must be determined for each attendee which customers should visit and in what order, so that all customers are served and the different restrictions for customers and attendees are respected. In our proposed solution, we seek to satisfy all patients by permitting them to be visited, as far as possible, by the staff of their choice. All patients should be treated during the day. Figure 2 displays an instance of the HHRSP with one home healthcare office and 14 visits.

To describe the mathematical model, we use the formulation of Kandakoglu et al. [30]. The problem is gotten as a one period that lets us to determine a list of day-to-day paths for caregivers. A caregiver circuit states when a precise caregiver must leave home, visit each allocated patient, and coming back home. The lists of patients and caregivers



Fig. 2 Example of solution description of the HHRSP



are designated by $P = \{1, 2, \dots, p\}$ and $N = \{1, 2, \dots, n\}$, respectively, where p is the patients number and n is the number of caregivers. The distance and travel time between the place l (domicile of the patient or the caregiver) and the place m (domicile of the patient or the caregiver), $l \neq m$, are noted, respectively, d_{lm} and t_{lm} . Subsequently, tours can take place at diverse times, and we accept that the distances and travel times are fixed throughout the journey. The cost of the trip is KM dollars per kilometer. The visit to the patient $i \in P$ necessitates st_i minutes and can only take place in the interval time $[a_i, b_i]$, where a_i and b_i are the oldest and most recent service start times for this patient. The interval $[ws_k, we_k]$ explains the time window through the caregiver k which is accessible to visit the patients. A meal break has a maximum length defined by LB minutes in the interval time $[al_k, bl_k]$. The trip time between the home caregivers and the main structure is designated by t_k . This parameter permits us to consider trip times when defining caregiver roads.

In the following, we describe all the notations, parameters, and decision variables used in the mathematical formulation of Kandakoglu et al. [30].

Notations	Description
P	List of patients
N	List of caregivers
V	List of $P \cup N$

Notations	Description
i, j	A patient $i, j \in P$
k	A caregiver $k \in N$
l, m	A location of patient or caregiver, $l, m \in V$
Parameters	Description
d_{lm}	Distance from l to m
t_{lm}	Travel time from l to m
a_i	Earliest service start time for the patient i
b_i	Latest service start time for the patient i
st_i	Duration of the visit i
t_k	Travel time from caregiver k 's home to the structure
ws_k	The start time of caregiver k
we_k	The end time of caregiver k
al_k	The earliest start time of caregiver k (mealtime break)
bl_k	The latest end time of caregiver k (mealtime break)
LB	Mealtime break duration
KM	Unit travel cost
OV	Unit overtime cost
M	A big constant M



Decisions variables

$$R_{ik} = \begin{cases} 1 & \text{if a caregiver } k \text{ can visit patient } i \\ 0 & \text{otherwise} \end{cases}$$

$$x_{lmk} = \begin{cases} 1 & \text{if a caregiver } k \text{ visit } m \text{ after } l \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1 & \text{if a caregiver } k \text{ take a break before visiting patient } i \\ 0 & \text{otherwise} \end{cases}$$

$$y'_{ik} = \begin{cases} 1 & \text{if a caregiver } k \text{ take a break after visiting patient } i \\ 0 & \text{otherwise} \end{cases}$$

s_{ik} = service start time for patient i if it visited by caregiver k

l_k = start time of mealtime break of caregiver k

$over_k$ = Total overtime essential from caregiver k

μ = Caregiver workload

The mathematical model given by Kandakoglu et al. [30] is given in the following:

$$\begin{aligned} \text{Min } & \lambda_1 \sum_{k \in N} \sum_{l \in V} \sum_{m \in V} d_{lm} x_{lmk} + \lambda_2 * KM \sum_{k \in N} \sum_{l \in V} \sum_{m \in V} d_{lm} x_{lmk} \\ & + OV \sum_{k \in N} over_k + \lambda_3 \sum_{k \in N} \sum_{l \in V} x_{lik} + \lambda_4 * \mu \end{aligned}$$

Subject to

$$\sum_{k \in N} \sum_{l \in V} x_{ilk} = 1 \quad \forall i \in P$$

$$\sum_{l \in V} x_{lik} = \sum_{l \in V} x_{ilk} \quad \forall i \in P, K \in N$$

$$\sum_{i \in P} x_{kik} \leq 1 \quad \forall K \in N$$

$$\sum_{i \in P} x_{ikk} \leq 1 \quad \forall K \in N$$

$$\sum_{i \in P} y_{ik} + \sum_{i \in P} y'_{ik} = \sum_{i \in P} x_{ik} \quad \forall K \in N$$

$$y_{ik} + y'_{ik} = \sum_{l \in V} x_{ilk} \quad \forall i \in P, K \in N$$

$$s_{ik} + st_i + t_{ij} \leq s_{jk} + M(1 - x_{ijk}) \quad \forall i, j \in P, K \in N$$

$$l_k + LB * y_{ik} \leq s_{ik} + M(1 - y_{ik}) \quad \forall i \in P, K \in N$$

$$\begin{aligned} s_{ik} + (st_i + t_{ij})(x_{ijk} + y_{jk} - 1) & \leq l_k \\ & + M(2 - x_{ijk} - y_{jk}) \quad \forall i, j \in P, K \in N \end{aligned}$$

$$\begin{aligned} l_k + (LB + t_{ij})(x_{ijk} + y'_{jk} - 1) & \leq s_{jk} \\ & + M(2 - x_{ijk} - y'_{jk}) \quad \forall i, j \in P, K \in N \end{aligned}$$

$$s_{ik} + st_i * y'_{ik} \leq l_k + M(1 - y'_{ik}) \quad \forall i \in P, K \in N$$

$$a_i \leq s_{ik} \leq b_i \quad \forall i \in P, K \in N$$

$$al_k \leq l_k \leq bl_k \quad \forall K \in N$$

$$ws_k - M(1 - x_{kik}) \leq \max\{(t_{ki} - t_k), 0\} \quad \forall i \in P, K \in N$$

$$\begin{aligned} ws_k - M(1 - x_{ikk}) + over_k & \geq s_{ik} + st_i \\ & + \max\{(t_{ik} - t_k), 0\} \quad \forall i \in P, K \in N \end{aligned}$$

$$LB + \sum_{i \in P} t_{ki} x_{kik} + \sum_{i \in P} \sum_{j \in P} (st_i + t_{ij}) x_{ijk} + \sum_{i \in P} t_{ik} x_{ikk} \leq \mu \quad \forall K \in N$$

$$x_{lik} \leq R_{ik} \quad \forall l \in V, i \in P, K \in N$$

$$y_{ik}, y'_{ik} \leq R_{ik} \quad \forall i \in P, K \in N$$

$$x_{lmk}, y_{ik}, y'_{ik} \in \{0, 1\} \quad \forall m \in V, i \in P, K \in N$$

$$s_{ik}, l_k, over_k, \mu \geq 0 \quad \forall i \in P, K \in N$$

4 Ant Colony System Methodology

This section describes how to tackle the VRPTW with synchronization visits in-home health care presented in the previous section using a hierarchical clustering technique based on an ant colony method. Ant colony-based optimization has been applied to a multitude of TSP combinatorial optimization problems [31], TSP with time windows [32], and VRPTW and PVRPTW (period VRPTW) [33]. ACS has been applied to conventional route optimization problems such as TSP and VRP and their variants with temporary windows. Till date, no relevant publication has been founded which attempts to solve the problem of planning home help with this type of metaheuristics. In this section, we have proposed an ant colony method with a clustering algorithm called ant colony system with clustering algorithm (ACS-CA for HHRSP), in which a greater number of modifications are made to improve performance and adapted to the particular characteristics of the problem being addressed.



4.1 Distributed Optimization

As described previously, the HHRSP is an NP-hard problem. A distributed optimization approach seems an adequate solution for this variant. The principal idea of this new approach is the decomposition of NP-hard problem into smaller subproblems while keeping the entire search space. This compromise between reducing complexity and exploring the solutions space has always been treated by researchers using different methods. Some works using local and global research have been proposed, and other solutions have been proposed as a hybrid approach which are applied for some optimization problems. Metaheuristic methods may have proven to be successful in the past, but sometimes this type of approaches presents some limits depending on the complexity of the optimization problem. Decomposing the problem space can increase the complexity. We propose also to solve different subproblems in a parallel way.

As illustrated in Fig. 3, our solution is composed by three parts. We begin by a clustering algorithm to decompose the space into some smaller zones. After that, each cluster will be treated by a Java thread that executes a basic ACS algorithm, and in a parallel way, our distributed algorithm executes a global research. All the local and global research threads use the same pheromone traces. It consists of the

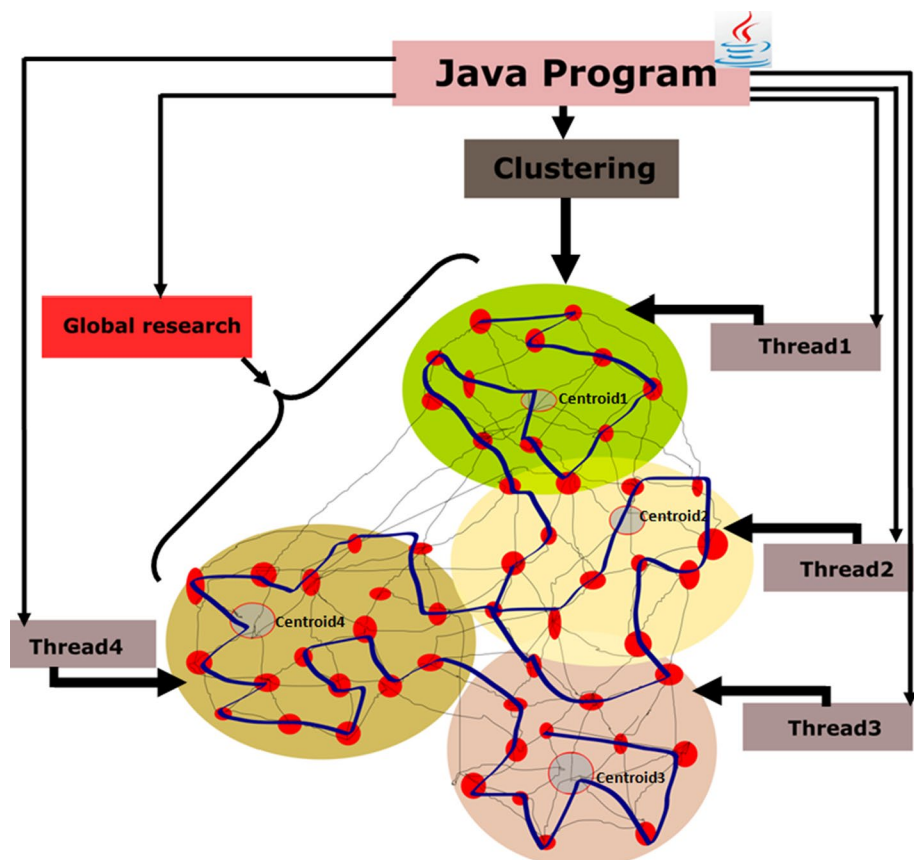
intelligent communication between the different parts of algorithm. Figure 3 shows the scheme of hybrid ACS-CA algorithm.

Both parts of algorithm (clustering and parallel ACS) will be hybridized to propose a new optimization approach.

4.2 Clustering Algorithm

For the clustering part, we apply the K-means algorithm. It is one of the popular unsupervised machine learning algorithms. The principle of this approach consists in a learning process that begins by random selection of centroids. These centroids will be used as the beginning points for every cluster, and then, iterative calculations are performed to optimize their positions. When there is no change in their values, the centroids can be considered as stabilized and the clustering is successful. Each patient is attributed to the closest cluster as described in the algorithm in the next box. The centroid is the center of the cluster, and his coordinates are calculated as follows: $(x_j, y_j) = \left(\frac{\sum_{i=1}^m x_i}{m}, \frac{\sum_{i=1}^m y_i}{m} \right)$ when x_i and y_i are the coordinates of each patient in the same cluster. In the following, we describe our k -means algorithm used in the clustering step:

Fig. 3 Scheme of hybrid ACS-CA algorithm



K-means Algorithm

```

1. Initialize cluster centroids randomly
2. Repeat until stabilization {
    2.1 For every patient calculate distance from every cen-
        troid
    2.2 Attribute every patient to the closest cluster
         $C(i) = \operatorname{argmin}_j d_{ij}$ 
    2.3 Update cluster (set of patients)
    2.4 Calculate the new centroid for every cluster
        The centroid  $C_j = (x_j, y_j) = \left( \frac{\sum_{i=1}^m x_i}{m}, \frac{\sum_{i=1}^m y_i}{m} \right)$ 
}

```

Each spatial grouping of patients will be considered as a class. It is obvious that optimization in a single class is easier, but it remains a local optimal that it will serve for a global optimization to be refined in parallel.

4.3 ACS Algorithm

The ACS algorithm is based on the use of pheromone for communication. It is very important in our distributed approach. It will serve as a link between local and global research. In each zone, the global research ants come across the pheromone traces left by local research ants and consequently the local optimal (the optimal path of the zone or cluster) will be favored.

When designing an ACS-based algorithm and applying it to the homecare planning problem, several issues will be considered. First, there are the details of how solutions are created and how agents, called ants, come up with these solutions. Each ant represents a complete and valid solution to the problem; in our case, it will be a set of clusters $C = \{c_1, \dots, c_k\}$, and each of them will consist of a set of services $c_k = \{s_1, \dots, s_m\}$. The solutions are obtained constructively as each ant moves through the vertices of the graph; the order of visit determines all the clusters obtained. Initially, each ant selects an initial vertex and incorporates it into a cluster c_0 which is initially empty. Thereafter, according to a probabilistic transition rule, it is selected which will be the next summit to visit, which will be part of the cluster under construction. Said process of incorporating vertices into the current cluster will end when a certain stop condition is met. Once this condition is met, the first cluster c_0 will have been formed, the cluster formation process will restart and repeat the formation of as many clusters as necessary, until all the patients of the graph will be visited.

In each thread, our classic ACS algorithm uses a set of ants. Each one chooses round journeys alongside with the patients. Two weights are associated for each edge between two patients. The first weight noted $\tau(i, j)$ is the pheromone

quantity which updated by ants at each crossing. The second weight noted $\eta(i, j)$ is the cost or the length of the edge. We begin by placing f ants in the depot. Each ant moves from patient to another until it creates a complete round. By using a probabilistic equation, an ant selects the next patient. This probability of choice is based on the edge length and pheromone quantity. Ants promote transition with great quantity of pheromone and short edge. The pheromone trail is updated when all ants have finalized their trips. Then, all the steps of transition and pheromone update will be repeated. Our AC0 algorithm (Algorithm 2) for HHRSP problem, using an initial solution given by the greedy constructive algorithm (GCA) (e.g., [5]), is described as follows:

Algorithm 2. ACS algorithm for HHRSP

```

01: Step 1: We initialize a set of ants for each cluster and a set of
    ants for global research in each depot
02: Step 2: We initialize a pheromone trail table
03: Step 3: Repeat until Convergence:
04: For each ant:
05: Repeat until the end of run:
06: We move from depot or patient to another according to the
    probabilistic equation
07: We move from depot or patient to another according to the
    probabilistic equation
08: We verify the run of each vehicle (capacity)
09: We update pheromone trail

```

4.3.1 Solution Representation

The solution is represented by vehicle. For each vehicle, the list of visited patients is given as a vector which contains their index number. If we suggest, for example, a HHRSP problem with five patients and three vehicles, a solution can be presented as follows (Fig. 4).

4.3.2 Selection

Whenever an ant starts looking for a new solution, the first step is to select an initial patient, and this patient will be included in the current cluster and will determine which other vertices can be visited. This strategy will be used

Patients		
Vehicle1	3	4
Vehicle2	1	2
Vehicle3	5	

Fig. 4 Solution representation



whenever it is necessary to form a new cluster. This selection is made taking into account the cardinality of each patient and a probability selection rule.

We chose to associate the patients with the groups to be assisted (the set G) before the respective structure. The graph is defined as $\Gamma' = (G \cup \{0\}, A')$, which is an undirected graph with no loop. The set A' basically represents the full allowed paths between the different patients with the structure denoted by $\{0\}$. Here,

- $\Gamma' = (G \cup \{0\}, A')$ is a completed graph
- $G \cup \{0\}$ represent the set of patients
- A' is the set of arcs
- For $\{g, h\} \subset G \cup \{0\}$ patients, the distance traveled between the patients of groups g and h is:

$$d_{gh} = \sum_{i,j=0}^{n \times n} e_{gi} e_{hj} d_{ij},$$

where e_{gi} is the group membership indicator g instead of structure i .

To move from one patient i to another patient h , we deploy transition logic with the basics:

- $J_f(g)$: set of summits that are still to be visited by the ant f , situated at the patient i .
- VIS_{gh} : the preference to add the arc (g, h) to create the solution.
- $p_{gh}^f(t)$: the probability that the ant f , placed at the patient g , at the immediate time t , travels toward the patient h .

The probability that patient is selected as the initial patient for a cluster is given by:

$$p_{gh}^f(t) = \begin{cases} \frac{[PQ_{gh}]^\alpha \times [VIS_{gh}]^\beta}{\sum_{f \in J_f(g)} [PQ_{gh}]^\alpha \times [VIS_{gh}]^\beta} & \text{if } h \in J_f(g) \\ 0 & \text{Otherwise} \end{cases}$$

The pheromone quantity PQ_{gh} indicate if we travel from patient i to patient j in relation to the coefficient α and the visibility VIS signify the advantage of traveling from patient i to patient j linked with β . We set the $VIS_{gh} = \frac{1}{d_{gh}} = \left(\sum_{i,j=0}^{n \times n} e_{gi} e_{hj} d_{ij} \right)^{-1}$.

The footprint of the pheromone is reset when the solution obtained is not able to improve for a maximum number of iterations. We apply the track update rule as follows: $PQ_{gh} = (1 - \rho)PQ_{gh} + \rho PQ_{gh}(0)$ where ρ is the evaporation rate (with $0 \leq \rho \leq 1$) and $PQ_{gh}(0)$ denote the initial value of the trails.

4.3.3 Local Search

As a local search in our algorithm, we have used two neighborhood operators noted N_1 and N_2 . The two neighborhood structures let us to concentrate on a new solution by applying permutation and insertion operators on the same route.

4.3.3.1 Neighborhood N_1 : Inter-route Permutation To improve the solution given by the ACS-CA algorithm, we use an inter-route permutation. Our local search (N_1) is illustrated in the following algorithm:

Algorithm 1. The inter-route permutation

```

01: BEGIN
02: For each vehicle  $k$ 
03: For each route  $T$ 
04:  $g \leftarrow 1$ 
05: Repeat
06:  $p \leftarrow 1$ 
07: Repeat
08:  $T' \leftarrow T$ ;
09:     Insert  $g$  in the position  $p$  in the route  $T'$ 
10:     If  $(F(T') < F(T))$ 
11:  $T \leftarrow T'$ 
12:      $g \leftarrow 0$ 
13:  $p \leftarrow$  Number of a group in  $T$ 
14: EndIf
15:  $p \leftarrow p + 1$ 
16: Until  $(p > \text{Number of group in } T)$ 
17:  $g \leftarrow g + 1$ 
18: Until  $(g > \text{Number of group in } T)$ 
19: EndFor
20: EndFor
21: END

```

4.3.3.2 Neighborhood N_2 : Two-opt-move The first local search used is defined by the $2 - Opt(k, k', r, s)$ operator who allows exchanging subsequence between two different routes $R(k), R(k')$; $k, k' \in \{1, \dots, K\}, k \neq k'$. The idea is to substitute two arcs, (i, j) and $(i + 1, j + 1)$ with two others arcs, $(i, i + 1)$ and $(j, j + 1)$, and the setback of the path $p(i + 1, j)$. Patients i on path $R(k)$ and patients j on the path $R(k')$ are swapped to obtain a savings cost. The better solution found to replace the current and the exploration continues (Fig. 5).



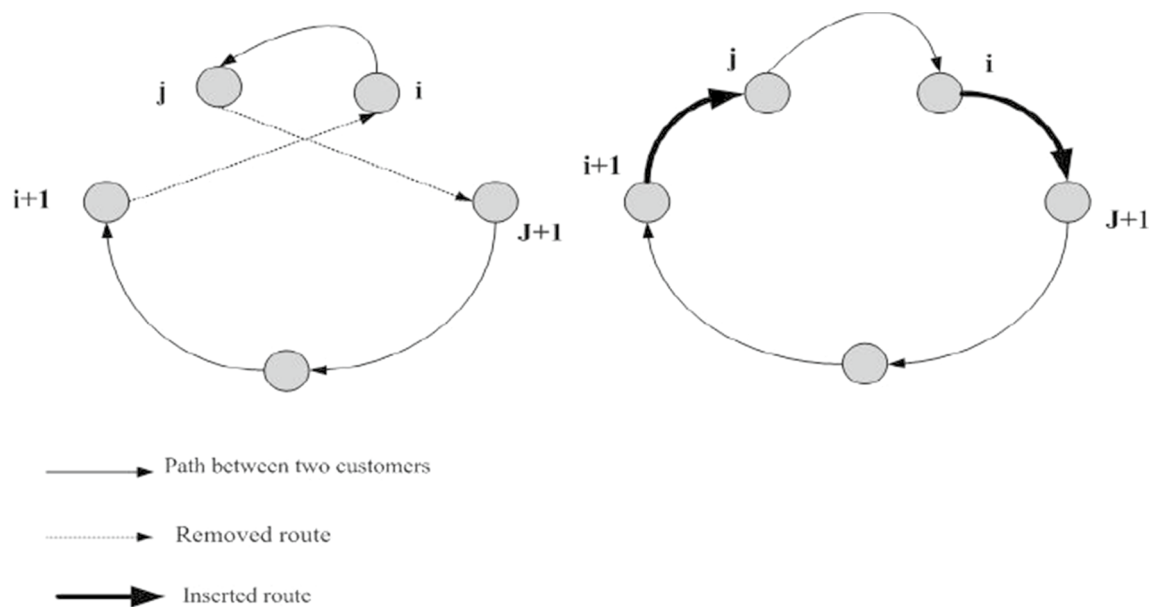


Fig. 5 Two-opt neighborhood. *Source:* Euchi et al. [11]

5 Computational Experiments

This section provides a detailed presentation of the results obtained by the ACS-CA proposed to solve the HHRSP. First, the different instances that will be subject to experimentation are presented, exposing their main characteristics, as well as a descriptive analysis of them. Subsequently, the sensitivity of the parameters of the ACS-CA technique that will be subject to experimentation and their configuration technique is presented. Finally, a comparative study is carried out between the ACS-CA techniques presented in the literature, and their performance is analyzed concerning other existing solutions such as the solution proposed by Afifi et al. [28] and Decerle et al. [34].

5.1 Instances

One of the most important characteristics of the dataset used to validate the proposed techniques is undoubtedly the great dimensionality of the instances. The examples present in the

state of the art and used to solve the planning problems of homecare assistants rarely exceed the hundreds of customers, and to date, no relevant publication has been found in which cases with more than 1000 clients have been resolved.

The proposed algorithm has now been tested on 30 datasets from Bredström and Rönnqvist [21]. The first grouping of data is based on the number of patients with different sizes of time windows. The visits are divided into three types which are called a group of type small (*S*), medium (*M*), and large (*L*), and are subdivided for each type into groups of instances according to the number of patients and the number of staff who will be independently resolved. Instances are grouped with clients equal to 20, 50, and 80 for each type of instance (*S*, *M*, and *L*). Table 1 describes the distribution with the characteristics of the sets of instances.



Type	Instance	Number of patients (N)	Number of staff members (K)	Synchronized visits (N_{SYNC})	Time windows (TW)		
					S	M	L
Small (S)	1	20	4	2	1.5	2.1	2.9
	2	20	4	2	1.8	2.9	3.9
	3	20	4	2	1.6	2.5	3.4
	4	20	4	2	1.5	2.4	3.0
	5	20	4	2	1.6	2.5	3.4
	6	50	10	5	1.4	2.3	3.1
	7	50	10	5	1.5	2.2	3.0
	8	50	10	5	1.6	2.5	3.4
	9	80	16	8	1.5	2.3	2.9
	10	80	16	8	1.5	2.3	2.9
Medium (M)	1	20	4	2	1.7	2.2	3.0
	2	20	4	2	1.3	2.1	3.2
	3	20	4	2	1.5	2.4	3.2
	4	20	4	2	1.8	2.9	3.9
	5	20	4	2	1.5	2.4	3.2
	6	50	10	5	1.6	2.5	3.4
	7	50	10	5	1.7	2.1	2.9
	8	50	10	5	1.5	2.4	3.2
	9	80	16	8	1.6	2.6	3.6
	10	80	16	8	1.8	2.6	3.4
Large (L)	1	20	4	2	1.5	2.4	3.0
	2	20	4	2	1.4	2.3	3.1
	3	20	4	2	1.7	2.2	3.0
	4	20	4	2	1.3	2.1	3.2
	5	20	4	2	1.7	2.2	3.0
	6	50	10	5	1.5	2.4	3.2
	7	50	10	5	1.4	2.3	3.1
	8	50	10	5	1.4	2.3	3.1
	9	80	16	8	1.7	2.4	3.5
	10	80	16	8	1.6	2.5	3.8

5.2 Parameters Sensitivity

Before analyzing the results obtained with the ACS-CA method, it is necessary to describe the parameterization used in the experiments, it is recommended to consult this for a better understanding of them. Table 2 describes the sensitivity of the parameters of our ACS-CA procedure.

The combinations of the above parameters give a total of six experiments. One of the aspects to be considered is the existence of a certain random component in the developed method. This component is due to how the links are resolved in the regrouping process; in this situation, it was chosen to choose one of them at random to study the impact on the quality of the solutions obtained. For this reason, the experiment of each of the above configurations was repeated ten times in total, which gives a total of 60 experiments.

5.3 Results

Once the parameters that have been used in the experimental phase for the ACS-CA method are presented, the results obtained are presented in Tables 3, 4, and 5 which contain all the results of the different runs and configurations with the different sizes of scenarios.

The proposed ACS-CA metaheuristic technique is implemented in Java and executed on Intel® Core™2 Duo Processor T5870 (2M Cache, 2.00 GHz, 800 MHz FSB) with 4-GB RAM. To solve the small tests, we have used the AMPL environment for all implementations, using CPLEX version 10.

As a result, we present a new ACS-CA optimization approach that we use in the experiments. Our proposed methodology can be compared with the SA-ILS metaheuristic, presented in Afifi et al. [28] and the results of Decerle et al. [34] (MA). We will use the notation OPT when we bring up to solving the datasets using CPLEX. The results are shown in summary in Tables 3, 4, and 5, showing the mean values (μ) and the standard deviation (σ) for each of the configurations.

To assess the performance of our heuristics (ACS-CA) with the approaches proposed in the literature [*simulated annealing-iterative local search* (SA-ILS), *memetic algorithm* (MA)], we summarize in Table 3 the results of small-type instances (Type S) by comparing the solutions obtained by our method with optimality results given by CPLEX and with the SA-ILS and MA approaches. Table 3 illustrates the mean and standard deviation of all instances. Table 3 shows that ACS-CA makes it possible to achieve very good results compared to the results obtained by the approaches (SA-ILS and MA on the same instances). Indeed, the average ACS-CA results for small-type tests are very important, and the rounds obtained by our method are of very comparable quality and are identical to those obtained by exact approaches (OPT). Among ten tests, the ACS-CA makes it possible to obtain eight new solutions better than the results proposed by the SA-ILS and MA approaches. Besides, unlike the exact approaches, we note that the variation in

Table 2 Parameters sensitivity of our ACS-CA procedure

Parameter	Description	Value
m	Ants number	8
Alpha	Pheromone quantity coefficient	0.75
Beta	Visibility coefficient	0.25
Iter_max	Maximum number of iterations	1500
Pheo_0	Pheromone initialization	0.45
r	Rate of evaporation	0.60
nr	Number of runs	10



Table 3 Comparison results of the scenarios for the small instances

Type	Instance	(N)	(K)	N_{SYNC}	OPT	Simulated annealing–iterative local search (SA–ILS)		Memetic algorithm (MA)		Ant colony system–clustering algorithm (ACS–CA)	
						Z	CPU (s)	Z	CPU (s)	Z	CPU (s)
Small	1	20	4	2	3.45	3.55	0.02	3.55	–	3.45	0.015
	2	20	4	2	3.85	4.27	0.02	3.94	–	3.85	0.018
	3	20	4	2	3.52	3.63	0.02	3.56	–	3.52	0.019
	4	20	4	2	5.77	6.14	0.02	5.77	–	5.77	0.017
	5	20	4	2	3.64	3.93	0.03	3.70	–	3.64	0.028
	6	50	10	5	–	8.1	13.97	8.03	–	8.1	11.38
	7	50	10	5	–	8.39	15.08	7.91	–	7.99	12.26
	8	50	10	5	–	9.54	25.13	9.02	–	9.02	19.83
	9	80	16	8	–	11.93	150.52	11.63	–	11.57	51.02
	10	80	16	8	–	8.6	16.1	8.80	–	8.6	9.55
Mean (μ)						6808	22,091	6591		6551	104,137
SD (σ)						2924	46,054	2876		2882	15,926

Table 4 Comparison results of the scenarios for the medium instances

Type	Instance	(N)	(K)	N_{SYNC}	OPT	Simulated annealing–iterative local search (SA–ILS)		Memetic algorithm (MA)		Ant colony system–clustering algorithm (ACS–CA)	
						Z	CPU (s)	Z	CPU (s)	Z	CPU (s)
Medium	1	20	4	2	3.44	3.55	0.02	3.48	–	3.44	0.021
	2	20	4	2	3.44	3.58	0.03	3.45	–	3.44	0.027
	3	20	4	2	3.31	3.33	0.03	3.33	–	3.31	0.026
	4	20	4	2	5.30	5.67	0.05	5.36	–	5.32	0.043
	5	20	4	2	3.44	3.53	0.03	3.49	–	3.44	0.025
	6	50	10	5	–	7.7	26.68	7.59	–	7.58	16.27
	7	50	10	5	–	7.48	18.34	7.25	–	7.21	15.13
	8	50	10	5	–	8.54	15.01	8.41	–	8.36	13.11
	9	80	16	8	–	10.92	292.17	10.90	–	10.90	92.65
	10	80	16	8	–	7.62	52.75	7.97	–	7.54	43.52
Mean (μ)						6192	40,511	6123		6054	18,0822
SD (σ)						2649	90,066	2673		2650	29,578

the complexity of the time dependencies has no impact on the calculation time of the ACS–CA. The CPU time execution of all instances obtained by our metaheuristics is better than the MA heuristics.

In the experiments given in Table 4, we tested our heuristic (ACS–CA) using instances of medium type (M), made up of 20–80 patients, and 4–16 caregivers with synchronization up to 8. Since the number of iterations in this type of instance is very large, we collect a sample of a thousand iterations. From which, we will assess the quality of the results obtained by the ACS–CA. We summarize in Table 4 the

results obtained by our metaheuristics. This table highlights that the ACS–CA approach gives in all tests, a better solution than that proposed by the SA–ILS and MA approach. Our ACS–CA approach with 6.054 on average is better than the other SA–ILS and MA approaches with 6.123 and 6.192, respectively. Table 4 shows that the proposed metaheuristics are very robust as regards the resolution of medium-sized problems.

Subsequently, we tested our heuristics on large-type instances (Table 5). The purpose of these experiments is, firstly, to test the robustness of our heuristics in the face



Table 5 Comparison results of the scenarios for the large instances

Type	Instance	(N)	(K)	N_{SYNC}	OPT	Simulated annealing–iterative local search (SA–ILS)			Memetic algorithm (MA)		Ant colony System–clustering algorithm (ACS–CA)	
						Z	CPU (s)		Z	CPU (s)	Z	CPU (s)
Large	1	20	4	2	3.32	3.39	0.03		3.32	–	3.38	0.022
	2	20	4	2	3.29	3.42	0.03		3.33	–	3.31	0.029
	3	20	4	2	3.27	3.29	0.02		3.28	–	3.29	0.016
	4	20	4	2	4.97	5.13	0.09		5.11	–	5.11	0.075
	5	20	4	2	3.27	3.34	0.03		3.31	–	3.31	0.023
	6	50	10	5	–	7.14	15.86		7.32	–	7.08	13.44
	7	50	10	5	–	6.88	15.92		6.83	–	6.83	13.67
	8	50	10	5	–	8	2.51		7.95	–	7.79	1.63
	9	80	16	8	–	10.49	207.17		10.34	–	10.32	87.43
	10	80	16	8	–	7.75	51.89		7.80	–	7.67	31.06
Mean (μ)						5883	29,355		5859		5809	147,395
SD (σ)						2534	64,554		2535		2485	27,500

of large instances (i.e., instances representing reality) and, secondly, to confirm the results obtained at the level of instances of the small and medium types.

In Table 5, The ACS-CA provides the best solutions for all large-type instances compared to the algorithms presented in the literature (SA–ILS and MA). We note that on average the solution given by our method (ACS-CA) is the best (with 5.809) compared to the results of the SA–ILS approaches [28] (with 5.883) and MA by Decerle et al. [34] (with 5.859). We note in Table 5 that our approach gives better solutions for all large-type instances with a minimum execution time while comparing with SA–ILS and MA.

From Tables 3, 4, and 5, we notice that our algorithm outperforms the algorithms (SA–ILS, MA) of Afifi et al. [28] and Decerle et al. [34] in terms of the objective function and calculation time. For the smallest and medium-sized instances (S , M) with 20 patients and two synchronized visits and four caregivers, an optimal solution was found, while near-optimal solutions with a fast turnaround time are obtained for the rest of the instances more than 20 patients. Also, we remark that the ACS-CA provides better solutions for all instances compared to the algorithms presented in the literature. We conclude that our ACS-CA method seems to be the best procedure that is effective and efficient to solve the HHRSP. The ACS-CA maintains a minimum deviation from the best known and optimal results for all sets of instances of different sizes.

The proposed technique (ACS-CA) is proved to be very efficient, both in terms of the quality of the caregivers' rounds and the calculation time to generate all the tours. Indeed, the tests carried out have shown that the heuristic makes it possible to generate solutions of fairly comparable quality compared to the approaches given in the literature,

i.e., the approaches based on MIP, and has a very reasonable computation times compared to the timing of the decision of the coordinating doctor responsible for making the daily schedules.

6 Concluding Remarks and Future Perspectives

Health is one of the powerful factors of social integration and cohesion, but also of generating wealth and well-being. However, home health care takes the form of home visits, whose scheduled visits vary according to the patient's care needs and must be established, consensually within and in a team, where the patient, caregiver, and/or family. Visits are generally planned manually, and the solution obtained may not be the best. In this logic, and in an attempt to reduce the elaborated costs, it is needed to use procedures that minimize the total time spent on the paths of home visits.

In this way, optimization becomes essential for health units that perform homecare services, about the planning and scheduling of nurses who provide health care during home visits.

A considerably important topic in healthcare was discussed in this paper. It consists of the planning of medical and/or non-medical visits under several constraints in-home health care with characteristics treated separately each to another. Ant colony system with cluster algorithm (ACS-CA) has been proposed. The objective is to solve home healthcare routing and scheduling problems (HHRSP). One of the major contributions in search algorithms we propose is the acquisition of polynomial memory through the ant colony principle. An ant colony heuristic-based



clustering algorithm has been addressed for a class of VRP with home healthcare problems. An encouraging result has been achieved through a variety of benchmarks comparing to some existing metaheuristic techniques. The local search technique approach is significantly effective in escaping poor local optima. Likewise, it is more robust in the principle of having remarkable results independent than having a good initial solution. Based on the results obtained, the proposed approach can be suggested in the planning of care and consequently the quality of nursing care. A conclusion seems to be suitable to judge that a hybrid metaheuristic approach can increase the performance of single metaheuristics. An interesting direction seems to be interesting in future work which consists of adding new procedures and low-level heuristic arrangements to properly discover the search space. Likewise, we hope to apply this approach to other variants of HHRSF.

As the objectives have been reached and the results are satisfactory, there are still aspects that can be improved so that the optimal home visit procedures in the health units can be even better in the future. A future perspective would be to reformulate the problem and take into account the number of vehicles available per caregivers because not all nurses or caregivers assigned to a day of home visits have a vehicle. Another perspective, a crucial need for health structures, would be to adapt the methodology and algorithm developed in a web application, where all the planning and the solutions obtained would be a point of manipulation and easy online logistics management, access, and display on any equipment with the internet.

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