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When Ants Take Care of Humans: ACO for Home-Care Services Planning Optimization

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Abstract

Current planning approaches for home care services do not generally support the social and human dimension of planning. They focus on optimization criteria that are easily quantifiable, such as the cost. Whereas other criteria such as the quality of the relationship between caregivers and beneficiaries or the satisfaction of the latter are important too as they can highly influence the planning. To address this issue, we investigate in this work the problem of planning optimization for home care service. We propose an extension of the classical ant colony optimization algorithms. Optimization is carried out by several classic criteria such as the cost along with social-based criteria such as the relationship between caregivers and beneficiaries. We also propose a flexible and expressive language to represent the constraints in the form of predicates that can include variables, constants and functions of the problem. This allows each organisation to add its own constraints.

Keywords:

Home Care Services (HCS), Constraint Satisfaction Problem (CSP), Ant Colony Optimization (ACO)

Introduction

In France, according to the National Institute of Statistics and Economic Studies, one in three inhabitants would be 60 years or older in 2050. A lot of these people are in a situation of loss of autonomy and need to receive medical or social care. However, the specialized organisations lack of available places. Consequently, Home Care Services (HCS) are more and more emerging and several types of organisations were created recently. These HCS organisations reduce the overload and indebtedness of hospitals and other institutions and provide a better environment for beneficiaries.

The management of these organisations and more particularly the caregivers interventions planning is complicated and is still largely done manually. A large number of constraints must be considered when producing the plan such as the satisfaction of caregivers, of beneficiaries, skill requirements, working time regulations, variable duration of acts, etc. The production of a plan becomes a big challenge, as we often have to deal with hazards such as the integration of new beneficiaries, lack of staff, and various unanticiped changes.

Automatic plan generation constitutes a great solution to this problem and several approaches are proposed in the literature [10,15,18]. An automatic planning system must be flexible to deal with the hazards of planning, robust to satisfy the various constraints and be executed quickly to deal with emergencies, changes, or event crisis situations.

Current planning generation approaches generally address easily quantifiable criteria such as the cost, the travel distance and the number of caregivers, etc. We advocate that social and human dimensions of the care acts have a strong influence on the planning and must be considered. The satisfaction of the beneficiaries and their relationship with the caregivers are, for instance, important criteria to take into account while planing the caregivers interventions. In addition, constraints addressed traditionnally do not cover all needs of the HCS organisations.

To address this issue, we explore the problem of planning optimization of HCS and we study the potential of Ant Colony Optimization (ACO) algorithms to solve these problems. We chose to represent the problem as a Constraint Satisfaction Problem (CSP). Indeed, it allows us to reuse many tools, approaches and theoretical results about resolution and computational complexity of the problem instances. Moreover, CSP is well adapted to manage the constraints separately from the problem resolution which allows to easily customize or add social and human constraints.

Organisation of the paper. Preliminaries section recalls some basic notions regarding HCS planning problem, CSP and ACO. ACO for HCS optimization section presents our optimization approach, while Experimental Results section exposes the system implementation, experimental results and feedbacks from a qualitative study. Related Work section discusses related works. We conclude and draw future work in Conclusion and Future Work section.

Preliminaries

We introduce and recall some basic notions regarding HCS planning problem, CSP and ACO in this section.

Home Care Services Planning Problem

Home Care Services (HCS) are paid care services, proposed to people in their home. A beneficiary is a person, who is subscribed to a home care service. A caregiver is a competent person that carries out the set of care acts. An intervention is a set of acts performed at a time t by a caregiver c for a beneficiary b. A planning constraint is a condition for carrying out one or more interventions.

The HCS planning problem consists in the definition of a set of interventions to meet the demands of a set of beneficiaries taking into consideration the optimization of the satisfaction number of planning constraint.

Constraint Satisfaction Problem (CSP)

A CSP [19,22] is well adapted to represent several real problems with constraints. A CSP is defined by a triplet (X, D, C) where:

- $X = \{X_1, X_2, \dots, X_N\}$ is a set of variables of the problem.
- D is a domain function that associates to each X_i its domain $D\ (X_i)$ (possible values of X_i).
- $C = \{C_1, C_2, \dots, C_M\}$ is a set of constraints of the problem.

The associated optimization problem consists in the assignment of the variables and in the optimization/satisfaction of a set of constraints or/and an objective function. It is also called constrained optimization problem (COP).

Ant Colony Optimization (ACO)

ACO [7,9] is a meta-heuristic for solving combinatorial optimization problems. It is inspired by the behavior of real ants when foraging. The first ant colony algorithm was proposed by Dorigo [6] to solve the travelling salesman problem which consists of finding the shortest route that visits each city of a given set of cities. The basic principle behind ACO is to produce a collective intelligence from the interaction of individual behaviors to solve a complex problem. Indeed, the behavior of a single ant is not complex, but the result of the collaboration of multiple ants results in the emergence of a complex collective behavior.

Ants foraging consists in finding a source of food and the shortest path between this source and the anthill. Ants converge progressively to the shortest path through an indirect communication mechanism called stigmergy, achieved by the modification of the environment. This mechanism is realized by the deposit of a volatile hormone (i.e. pheromone) on the path taken by the ant. This pheromone has a direct impact on the behavior of the following ant, as they are attracted by the pheromone and more likely to move towards it. This results in ants following the same path as the first ant, but the decision remains stochastic, since other ants take other paths. An important characteristic of the pheromone lies in its ability to evaporate quickly. This makes the less traveled paths disappear (often the longest), and increases the amount of pheromone deposited on the shortest paths, because more and more ants take these paths. This phenomenon allows a short path to emerge (not necessarily the shortest possible path) that almost all ants follow even if some ants take other paths.

It is important for this type of approach to find a good balance between intensification (i.e. exploitation of collected information) and diversification (i.e. exploration of the research space). For ACO, intensification is realized by the deposit of pheromone and diversification through stochastic decision making of ants and the evaporation of pheromone.

Related Work

HCS planning problem is a problem with an exponential number of candidate solutions. Each candidate solution is evaluated, the goal is to find the best rated candidate solution. Intuitively, the resolution consists in listing all the candidate solutions and take the best rated one, but this is not possible in a reasonable time. The complexity [17] of this type of problem is in general *NP-complete* or *NP-hard*.

To design a HCS planning system, we need to answer three key questions: (i) What are the planning constraints ? (ii) How to evaluate a plan ? and (iii) how find the best plan ?

These questions are highly linked to each other, they represents what constitutes a HCS planning system. We investigate a brief overview of the possible answers to the above mentioned questions. The first question concerns the planning constraints of a HCS planning problem, the second question concerns the evaluation criteria of a plan and the used evaluatio function, and the third question concerns the used resolution approaches:

i. HCS planning constraints: they are conditions related to the validity or the quality of the plan. Some conditions must be verified, and others are related to the quality of the plan. The most used constraints in the literature are [5,10,15]: skill requirements, sectors, temporal dependency, time windows, continuity of care, workload balancing, breaks, etc.
ii. Evaluation function: an important factor in HCS planning system is the evaluation function. This function defines the criteria to optimize when generating a plan. Several criteria are used in the literature as [10,15,18]: number of caregivers, travel time, travel time, waiting time, preference, constraint violations, etc.
iii. Resolution approaches: Solving a HCS planning problem consists in finding the best solution optimizing one or more given evaluation criteria from an exponential set of candidate solutions. This set of candidate solutions is called the problem research space. Resolution approaches can be classified according to Completeness and Correctness [18,22]: a correct and complete approaches, a correct and incomplete approaches and an incorrect approaches. The approaches used are generally correct and incomplete, we can cite [5,10,15,18]: tabu search, genetic algorithm, greedy search, local search, adaptive large neighborhood search, etc.

As mentioned before, current planning approaches do not generally support the social and human dimension of planning, while the relationship and the satisfaction of the beneficiaries and the caregivers are very important. In addition, the constraints are very general and do not cover all needs of the HCS organisation.

ACO for HCS optimization

Our choice to represent the problem as a CSP enables us to separate the problem from the application field in order to better manage the representation of constraints and to simplify the adaptation of the solution to other applications. This information structure allow use to easily redefine constraints when required, to adapt the algorithm to different practices in different home-care organisations. About the resolution algorithm, ACO, has been used to solve several optimization problems [8,9,24], and also been successfully used to solve CSPs [13,21,22], which strengthens our choice. This naturally appeared as a relevant solution to our problem.

We present, next, our representation of the problem and BL-ANT-Planning, the proposed resolution mechanism.

Problem Representation

In the following, the representation of our problem in the form of a CSP. We have defined the variables of the problem, the function that associates each variable with its domain and the constraints of the problem.

Variables

We use a matrix $Assign[][]$ and an array $Planify[]$ to represent the variables of the problem, their size are $N \times M$ and N respectively, where N is the number of interventions and M is the maximum number of caregivers needed to perform an intervention.

- $Assign[1 \dots N][1 \dots M]$: it is the assignments of the interventions to the caregivers. $Assign[i][j]$ is the caregiver j who will perform the intervention i, such that $0 \le i < N$ and $0 \le j < M$.

- $Planify[1 \ldots N]$: it is the plan time of an intervention. $Planify[i]$ is the time slot identifier of the intervention i, such that $0 \leq i < N$. This identifier can be converted to a schedule.

Variables Domains

Let N be the number of interventions and let M be the maximum number of caregivers needed to perform an intervention, the function D that return the possible values of $Assign[][]$ and $Planify[]$ is defined by:

- $D(Assign[i][j]) = \{0, 1, 2, \ldots, K\}$ such that K is the number of caregivers and $0 \leq i < N$ and $0 \leq j < M$.
- $D(Planify[i]) = \{0, 1, 2, \ldots, T\}$ such that T is the number of time slots and $0 \leq i < N$.

Constraints

Let N be the number of interventions and let M be the maximum number of caregivers needed to perform an intervention. We define an expressive language to represent the constraints in the form of predicates that can include variables, constants and functions of the problem. For example:

- $\forall i \in [1;\ N], \forall j, k \in [1;\ M], if\ j \neq k$ $then\ Assign[i][j] \neq Assign[i][k]\ or\ Assign[i][j] = 0$ which means that an intervention cannot be assigned more than once to a caregiver.
- $\forall i \in [1;\ N], \forall j \in [1;\ M]$ $then\ Qualif\ (i) \subset Qualif\ (Assign\ [i]\ [j])$ where $Qualif\ (i)$ is a function that returns the skills of a caregiver (or necessary skills of acts), which means that a caregiver must have all necessary skills to perform care acts.

Based on that constraint representation, our test involve more than 17 constraints.

BL-ANT-Planning

Algorithm 1 describes the general principle of the approach. A first step (lines 2 and 3) for initializing the algorithm parameters and the pheromone. Then for each cycle (line 6), the ants generate solutions (one solution per ant) and each solution is improved by a local search (line 7). The solutions are then evaluated to update the best solution of the algorithm and the best solutions of the cycle (line 8). At the end of a cycle (line 9), the ants that have generated the best solutions of the cycle depose a pheromone. Finally, the best generated solution is then returned (line 10).

Initialization

In this step, the parameters of the algorithm are initialized and the pheromone is deposited on the possible solutions. Parameters include the number of cycles, the number of ants to use per cycle, the pheromone factor weight and the heuristic factor weight.

Algorithm 1: BL-ANT-Planning

```
   Input: problem : the input data of the problem
   Output: bestSolution : the best generated solution
1  begin
2      parameterInitialization(problem);
3      pheromoneInitialization(problem);
4      for i ← 0 to numberOfCycles do
5          for j ← 0 to numberOfAnts do
6              solution ← buildSolution(problem);
7              solution ← localSearch(problem, solution);
8              updateBestsSolution(solution, bestSolution, bestSolutionsOfCycle);
9          pheromoneUpdate(problem, bestSolutionsOfCycle);
10     return bestSolution;
```

Other parameters related to the pheromone are also initialized, the minimum pheromone factor and the maximum pheromone factor that can be found on a solution and the pheromone evaporation rate. Initially, a quantity equal to the maximum pheromone factor is deposited on all solutions.

Solution Generation

To generate a solution, the ant generates an assignment of the variables of the problem satisfying the constraints of the problem. What it generated is ignored if an assignment violates a constraint. The assignment is generated by assigning the variables one by one until there are no variables to assign. The order of the variable assignments is important, an assignment of a variable can restrict the domain of another variable or even make it empty.

1. *Variable selection:* the variable selection technique impacts the performance of the algorithm and the quality of the solution. Several techniques are proposed in the literature [3,19,23]. For performance reasons, we use for now a random selection of variables, where each variable has the same probability of selection. We plan to explore other selection techniques in future works.
2. *Value selection:* the value of the variable is selected from the subdomain that is compatible with the constraints of the problem. The value selection is stochastic and is based on the pheromone factor, deposited between the variable and its possible values, and on the heuristic of assignment evaluation. The probability of selecting the value v_i for the variable V_j is equal to: $p(v_i \to V_j) = \frac{[\tau(v_i \to V_j)]^{\alpha} \times [\eta(v_i \to V_j)]^{\beta}}{\sum_{v_k \in D_{V_j}} [\tau(v_i \to V_j)]^{\alpha} \times [\eta(v_i \to V_j)]^{\beta}}$

Where $\tau(v_i \to V_j)$ is the pheromone factor between v_i and V_j, $\eta(v_i \to V_j)$ is the heuristic factor of the assignment $v_i \to V_j$, α is the pheromone factor weight, β is the heuristic factor weight and D_{V_j} is the subdomain of V_j which is compatible with the constraints of the problem.

Improvement Solution

Local search is used to improve the solutions. It is performed before the solution evaluation in order to improve the ant generated solution. Caregivers satisfaction criterion is improved in this step by trying to eliminate unnecessary breaks.

Solution Evaluation

The solutions are evaluated in this step to keep the best solution of the algorithm and the best solutions of the cycle. Several criteria are used to evaluate a solution, including social and human dimension criteria. For example, the cost, the quality of the relationship between the caregivers and beneficiaries, the respect of the geographical area, the satisfaction of caregivers and beneficiaries, etc. Each criterion is evaluated on a scale of seven levels [1,16]. Then, an average of all criteria is calculated according to the weight of each criterion, this average will represent the evaluation of the solution.

Table 1. *List of identified planning constraints and optimization criteria.*

Related to	Planning constraint	Optimization criteria
Beneficiary	Time constraints and absences, state of the beneficiary and his entourage	Time preferences, regularity of the caregivers and plans
Caregiver	Qualification/skills, respect of employment contracts, lunch break, absences	Optimization of employment contracts, time preferences
Intervention	Synchronization with external services, caregiver/beneficiary incompatibility, replacement degree, equipment, travel time, mutual plans, implementation interval, intervention difficulty	Intervention priority, hardness
Organisation	Travel time, legislation, work rate, schedules of external structures	Compactness, costs, caregiver contract, sectors, substitute preferences

Pheromone update

At the end of a cycle, the pheromone factor is updated. A quantity evaporates and another quantity is deposited on the best solutions of the cycle. After each update, all the pheromone factors must be between the predefined minimum pheromone factor and maximum pheromone factor.

The evaporation of the pheromone is simulated at the end of each cycle by the multiplication of the pheromone factor by the pheromone evaporation rate. The pheromone deposit is not carried out as in nature, it is delayed until the end of the cycle and only performed on the best solutions of the cycle. The quantity of pheromone deposited depends on the quality of the solution. Pheromone deposition is only performed for the best solutions of the cycle unlike natural ants that deposit pheromone in all cases. We think this will help a faster emergence of solutions, we also plan to test other strategies.

Implementation

Our solution is implemented as a black-box service which takes as input a file formatted as JSON, specifying the list of caregivers, beneficiaries and the constraints to consider. The solution outputs a set of calendar files in iCal format. Each iCal file represents the plan of one caregiver.

The architecture of the application is modular, the definitions of the problem, of the constraints and of the resolution algorithm are decoupled. The software architecture make it also easy to integrate another resolution algorithm (i.e. other than ACO, such as genetic algorithm for instance), we can also change the representation language of constraints to cover a more expressive or less expressive language for better performance. This allows us to easily adapt our implementation to other applications and other problems.

Results

We test our approach in a twofold perspective. First, we did a quantitative study, focusing solely on algorithm performances. We then organised workshops with some HCS organisations to qualitatively test the algorithm on real cases. This enabled us to customise the solution evaluation function in order to improve the selection of solutions. This also allowed us to verify the accuracy and the usability of the proposed approach with practitioners.

Quantitative study

We started by studying for real case of planning, the influence of the algorithm parameters on the quality of the generated plans and the research quality. The quality of the generated plans is evaluated on the optimization criteria that we present in the following section and the research quality is measured by [4,11,20]: (i) a similarity ratio, in order to know if the collected information is well exploited and (ii) a resampling ratio, used to know if the research space is well explored by the algorithm. The best algorithm parameters found is (4, 2, 0.05, 0.1, 10) represents respectively the values of: 1) pheromone factor weight, 2) heuristic factor weight, 3) pheromone evaporation rate, 4) minimum pheromone factor and 5) maximum pheromone factor.

Regarding performance, we ran the algorithm on a machine with a 2.7Ghz i7-7500U processor and 16 GB of RAM. For an organisation with 268 beneficiaries, 37 caregivers, and 142 interventions to plan, the execution lasted 2 minutes for 10000 cycles with 15 ants by cycle.

We have a promising first results. They, nevertheless need to be consolidated and compared with other approaches. We have identified some benchmarks [2,12,14] for this comparison.

Qualitative study

We worked with five HCS organisations, initially to determine the planning constraints and optimization criteria they use. These HCS organisations are in different cities and are different size. The number of beneficiaries managed varies from 200 to 700 with 30 to 100 caregivers.

Table 1 lists the planning constraints and optimization criteria used by the five HCS organisations. Note that, a slight difference between the supported constraints list and the importance of each optimization criteria of the HCS organisations, this difference is related to the localization and the size of the HCS organisations.

We then tested the algorithm on the data of these organisations and we compared the generated plans with the plans they generate manually.

Table 2 presents a result of a comparison for an organisation with 268 beneficiaries, 37 caregivers, and 142 interventions to plan. This comparison is based on the number of caregivers needed for planning, the duration of all breaks and the regularity of interventions, such that an intervention is regular if the caregiver provided a car for the beneficiary at least twice.

Table 2. *Comparison of generated plans with organisations plans*

	Organisations plans	Result at 2min	Result at 30min	Result at 60min
Number of caregivers	21	19	16	15
Duration of all breaks	3120	3560	2660	2240
Number of regular intervention	140	142	142	142

The first results are promising, we improve the three criteria after 100000 cycles (30 min) and two criteria after 10000 cycles (2 min). Note that the number of regular interventions converges quickly, we cover 100% of interventions directly after 10000 cycles. These results remain to be confirmed on benchmarks.

Our results indicates that our solution generates plannings which are alsmost as good as the one done manually after only 2 min of computation with a standard computer. Furthermore, it also shows that after 60 mins of computation it provides solutions involving potentially 28% less caregivers. This could results in better service allowing caregivers to spend more time with beneficiaries and/or cheaper home-care service.

Conclusion and Future Work

In this paper, we proposed and implemented a resolution algorithm for the planning problem in the context of Home Care Services, based on Ant Colony Optimization. We used a Constraint Satisfaction Problem to represent the problem. The implemented application is structured into modules to facilitate its extension and adaptation to other problems. Since the algorithm is non-deterministic with a stochastic solution construction, the correct parameterization that is at the core of the mechanism needs to be further validated.

The next objective of our project is to compare the performance of our approach with other approaches on benchmarks. We plan also to study the impact of different parameters and try other pheromone deposition techniques or variable selection strategy. We will also look at what is done on CSPs in terms of filtering variables domains, representation and constraints management.

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