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Case-Based Reasoning for Home Health Care planning considering unexpected events

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Abstract: In recent years, Home Health Care (HHC) has gained popularity in different countries around the world (e.g. France, US, Germany, etc.). The HHC consists in providing medical services to patients at home. During the HHC service, caregivers' planning may be disrupted by some unexpected events (e.g. urgent request, caregiver absence, traffic congestion, etc.), which makes HHC activities infeasible. This paper addresses the daily HHC routing and scheduling problem by considering unpredicted events. To solve this problem, we propose a Case-Based Reasoning (CBR) methodology. Our purpose is to create the HHC case base which contains the knowledge about the perturbation.

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Keywords: Home health care, routing and scheduling problem, unexpected events, Case-Based Reasoning.

1. INTRODUCTION

Home Health Care (HHC) has been a significant alternative for providing medical health services at home, especially in light of the emergence of COVID-19 pandemic. It offers medical care and support services to patients at home (Martinez et al., 2019). Each caregiver visits a set of patients who need several services depending on the patients' need, such as home physiotherapy, speech therapy, nursing, activities of daily living (walking, bathing, and dressing), etc.

This study focuses on the HHC routing and scheduling problem. It is the major challenge in the HHC planning system. The HHC scheduling and routing process can be divided into two phases: an offline phase, which consists in generating an initial HHC routing plan for patient visits, and an online phase, which is based on rescheduling the current healthcare routing plan while considering unexpected events (e.g. car accidents, absence of caregiver, emergency or unavailable patients, etc.). Therefore, an effective solution is needed to adjust the current plan with the new changes.

The aim of this paper is to suggest a CBR methodology for the online HHC planning. The purpose is to build the HHC case base to quickly react and reschedule the disrupted activities caused by unexpected events. The goal is to reduce caregivers' delays in arriving at patients' homes while maximizing patients' satisfaction.

This paper is structured as follows: Section 2 reviews the related works. Section 3 presents the CBR methodology

for HHC planning. Section 4 introduces an example of case representation for the urgent request scenario, and section 5 consists the conclusion.

2. LITERATURE REVIEW

In this section, we present a brief description of the CBR methodology. Existing studies apply the CBR for the combinatorial optimization problems followed by the contribution of this study.

2.1 CBR overview

Case-Based Reasoning (CBR) is an Artificial Intelligence (AI) methodology, inspired from human reasoning (Kolodner, 1992). The aim is to solve a new problem by adapting solutions of previous similar problems (cases). The previous problems and their associated solutions are stored as "cases" in a database, called as "CASE BASE".

The CBR involves 5 phases, as illustrated in figure 1, and these phases are: refine, retrieve, reuse, revise and retain. The refine phase consists of representing the cases in the case-base in the same form. The retrieve phase consists of searching and selecting the most similar cases to the new case from the CASE BASE based on the similarity measure between older cases and the new case. In the reuse phase, these retrieved data and solutions are then used to adapt a new solution to the current problem. The revise phase consists in evaluating the new proposed solution. In this last phase, the new proposed solution is stored in the case-base in order to be used to solve future problems.

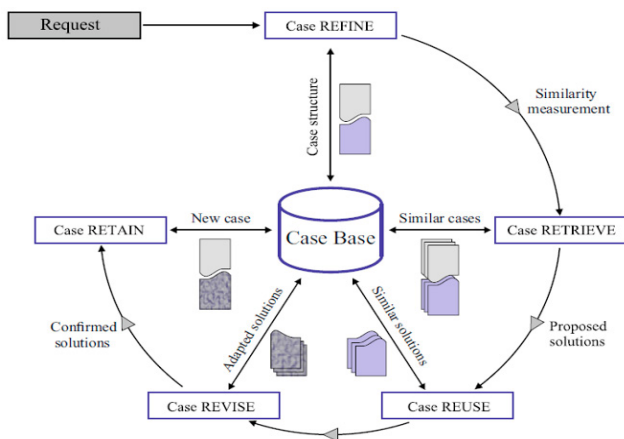


Fig. 1. The CBR process (Khosravani and Nasiri, 2020)

The CBR methodology has been applied in different domains, such as in recommender systems (Wongpun and Guha, 2017), disruption management (Louati et al., 2016), medical diagnosis (Gómez-Vallejo et al., 2016) and weather forecast (Ji et al., 2005).

2.2 CBR related work

The HHC scheduling and routing problem can be viewed as a combination of the Nurse Rostering Problem (NRP) and the Vehicle Routing Problem with Time Windows (VRPTW) (Yuan and Fügenschuh, 2015).

In the literature, few studies have used CBR methodology to solve the NRP. In (Beddoe et al., 2009), the authors used the CBR to create the nurse schedule by reducing the constraint violations. Each case is represented as the constraint violation and its associated repair. They implemented a memetic algorithm to evolve the good quality of repairs.

Recently, Simić et al. (2020) applied the CBR to solve the Nurse Scheduling Problem (NSP). They aimed to find the optimal plan for nurses in a hospital, taking into account the working day constraint. Cases are represented by a case number, nurse-ID, date, working shifts and its associated solution. Also, they combined CBR with the general linear empirical model with arbitrary coefficients to calculate the weighted value for working day shifts (either day shifts or nights or days off). Their model is tested with an original real data set obtained from the Oncology Institute of Vojvodina (OIoV) in Serbia.

In the Vehicle Routing Problem with Time Window (VRPTW), Quirion-Blais and Chen (2021) proposed a CBR approach for online retailing company. Their goal is to generate new routes based on the previously performed routes. Each route is regarded as a case stored in the case base. For a new VRPTW to solve, the associate solution corresponds to a set of routes visiting all required customers. The authors developed a MIP (Mixed Integer Programming) formulation for the retrieve phase in order to maximize similarity between the retrieved routes and the new problem. The BonoAlgorithm is used to evaluate the performance of the CBR methodology.

The reviewed studies did not take into account the dynamic aspects related to both problems (e.g. arrival of new requests, caregiver absence, traffic congestion, etc.).

2.3 Contribution of this work

According to Table 1, most of the existing research dealing with the dynamic aspects of the HHC scheduling problem has used metaheuristic methods to solve it. However, Alves et al. (2019) and Koh et al. (2020) highlighted in their literature reviews that these methods have a high response time, due to unexpected events, to provide the optimal solution.

Table 1. Overview of some recent literature research

Reference	Problem	Solution method
Du et al. (2017)	HHC	M
Marcon et al. (2017)	HHC	Sim-MAS
Ng et al. (2017)	VRPTW	M
Nasir and Dang (2018)	HHC	M
Ben Hassen et al. (2019)	HHC	M
Ouertani et al. (2019)	HHC	M
Ben Bachouch et al. (2020)	HHC	M
Simić et al. (2020)	NSP	CBR
Demirbilek et al. (2021)	HHC	M
Yalçındağ and Lanzarone (2021)	NSP	MILP
Quirion-Blais and Chen (2021)	VRPTW	CBR
Our approach	HHC	CBR

M: Metaheuristic; Sim-MAS: Multi Agent System Simulation; MILP: Mixed Integer Linear Programming model.

Moreover, these methods did not take the full advantage of all the information available, especially the past experiences during the execution of the system (Bono et al., 2020). Thus, the AI techniques can generalize from past experiences and quickly provide a decision for a new problem. As previously stated, the CBR is a paradigm of AI. According to the survey of Jubair et al. (2018), the CBR is based on the use of memory to solve a new problem, where it can use and adapt the solution from previous cases. Unlike other Machine Learning (ML) techniques (e.g. Artificial Neural Network (ANN), Rule-Based Reasoning (RBR), etc.), they begin from scratch to build a solution for a new problem. The CBR differs from other ML approaches in the learning process. The ML methods require a special training phase, which is applied once from large datasets, to make future predictions, while CBR learns from previously processed cases, and the knowledge is progressively acquired (Feuillâtre et al., 2020).

Additionally, solving problems in real-time becomes a major challenge, especially in a dynamic environment where no complete knowledge of the domain is available (Sarkheyli-Hägele and Söffker, 2020). Therefore, the CBR is able to reason with few known cases and build its knowledge incrementally as cases are added. Also, this technique is able to learn over time by memorizing the new cases that increase the system's ability to solve future problems. In contrast to the other ML algorithms, whenever information is extracted, a specific training phase is required, which makes on-line adaptation difficult (Pantic, 2006).

In this regard, the main contribution of this paper is:

- (1) To construct the case base for the HHC planning considering the unexpected events
- (2) To implement an online routing algorithm to reschedule the disrupted routes based on the initial planned routes

In the following section, we describe our proposed approach.

3. THE CBR APPROACH FOR HHC PLANNING

In order to cope with unexpected events, the purpose is to design an efficient decision support system to solve the online phase of the HHC routing and scheduling problem. The proposed approach is based on the CBR methodology in order to react instantly to these events. Figure 2 presents our CBR system. The initial routing plan is generated using the artificial immune algorithm developed by Ben Hassen et al. (2019). For each perturbation that happens, a new case is detected. An online routing algorithm is then executed to reschedule the planned routes based on the previous similar affected routes in order to ensure a robust decision to reduce the delay of caregivers' services and to maximize patient's satisfaction. Therefore, this paper focuses on the representation and retrieval phases of the proposed HHC planning system. The following subsections detail these two steps.

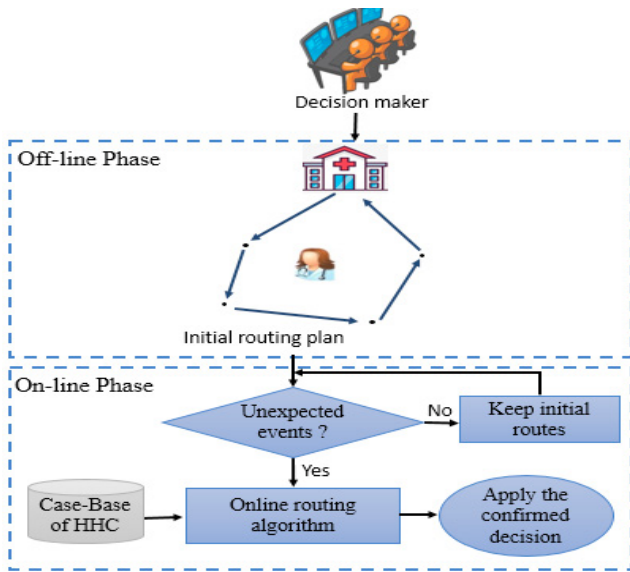


Fig. 2. HHC planning system using CBR

3.1 Refine Phase

The refine phase is the most critical decision in the construction of the CBR systems (Pal and Shiu, 2004). The representation of cases depends on the type of important features that represent the problem. A large variety of representation formalism exists, such as feature vector cases, structured cases, or textual cases (Richter and Weber, 2016). In this research, the cases depend on several features and values that describe them. Therefore, cases are represented as feature vectors. In general, for feature vector representation, the cases are represented as tuples of problems and their associated solutions.

In our context, each case is represented as a vector of Perturbation (P) and Decision (D), as formulated in the equation (1).

$$case(C) = \langle P; D \rangle \quad (1)$$

Where:

- P is the Perturbation that disrupts the work of the caregiver.
- D is the associate Decision.

Representation of the Perturbation (P) The P is described by a set of features. It can be grouped into 4 main groups, as formulated in equation (2),

$$P = \langle CI; PI; SI; TP \rangle \quad (2)$$

Where:

- CI is the Caregiver Information.
- PI is the Patient Information.
- SI is the Service Information
- TP is the Type of Perturbation.

The CI includes several variables that describe the caregiver, as presented in the formula (3).

$$CI = \langle CID; QC; CL; Gender; GIR_{list}; L; work_{day}; work_{hour}; time_{lunch}; time_{travel} \rangle \quad (3)$$

Where:

- CID is the Caregiver's IDentifier.
- QC is the Qualification of Caregivers (1 = general physician, 2 = special physician, 3 = nurse, 4 = auxiliary nurse).
- CL: is the current Caregivers' Location based on the longitude and latitude coordination coordinates.
- Gender: is the gender of the caregiver (0 = male, 1 = female).
- GIR_{list} : is a list of the various levels of dependency that the caregiver can consider.
- L: is the List of patients to be visited by the caregiver.
- $work_{day}$: is the working day of the caregiver.
- $work_{hour}$: is the caregiver's daily working hours.
- $Time_{lunch}$: is the time for the daily lunch break: $time_{lunch} = [l_{begin} = 12am, l_{end} = 14pm]$.
- $time_{travel}$: is the total traveling time.

The PI involves different features that describe the patient, as presented in the formula (4).

$$PI = \langle PID; GIR; TW; PR; GL \rangle \quad (4)$$

Where:

- PID: is the Patient IDentifier.
- GIR: is a level of dependency of patient. It ranges from 1 = high level to 6 = low level.
- TW: is the patient's preferred time window.
- PR: is the preference of the patient (e.g. gender of caregiver).
- GL: is the patients' home location based on the longitude and attitude coordinates.

The SI outlines the data of the service. It is defined by various attributes, as formulated in the equation (5).

$$SI = \langle s_{type}; s_{degree}; require_{caregiver}; s_{duration}; service_{start} \rangle \quad (5)$$

Where:

- s_{type} : is the type of service required by the patient (1 = home physiotherapy, 2 = speech therapy, 3 = nursing, 4 = blood pressure monitoring, 5 = home health aides (walking, bathing, and dressing)).
- $require_{caregiver}$: is the number of caregivers required to perform the service.
- s_{degree} : is the priority of the service (1 = urgent degree, 2 = medium degree, 3 = low degree)
- $Service_{duration}$: is the duration of the service.
- $service_{start}$: is the starting time of the service.

The TP is a vector of four main types of perturbation, as formulated in the formula (6).

$$TP = \begin{cases} 1, & \text{if the perturbation occurs.} \\ 0, & \text{otherwise.} \end{cases}$$

$$TP = \langle UR; NC; AV; PTW \rangle \quad (6)$$

Where:

- UR: is the new Urgent Request.
- NC: is the uNavailable Caregiver.
- AV: is the Accident eVents: car accident, traffic congestion, and weather conditions.
- PTW: is the change in Patient Time Window.

Representation of Decision (D) The decision refers to rescheduling the remaining planned patients during the day. We consider 5 possible actions in order to make the best decision. The decision can be a combination of more than one of following actions.

- Wait and then follow the planned route: If the disruption does not have a significant impact on the next visits, the caregiver can wait and then proceed the initial planned route.
- Insert the new request in the route: add the new request in one of the current routes
- Change caregiver: replace unavailable caregiver with available one.
- Reschedule the route: re-plan some affected visits
- Change some long visits: replace some long visits at the end of the day.

3.2 The retrieval phase

Once the features are identified and well represented, the next phase consists of retrieving the most similar perturbation cases from the HHC case base. The selected cases are retrieved based on the similarity measure. This latter is used to quantify the degree of resemblance between a pair of cases (Liao et al., 1998). The similarity value ranges from 0 to 1, with values close to 1 indicating that the cases are similar. The measure of the similarity depends on the global and local similarity functions.

The global similarity refers to the similarity value between the new case and the retrieved cases. The global similarity can be calculated by (7)

$$GlobalSim(nc, pc) = \sum_{i=1}^m Sim(nc_i, pc_i) \quad (7)$$

where, nc and pc represent respectively the new and previous cases, nc_i and pc_i are respectively the i th features of nc and pc . $Sim(nc_i, pc_i)$ represents the local similarity between the new case nc and the previous case pc .

For the feature vector representation, the local similarity is normally computed as an aggregation of attribute differences between two cases (Núñez et al., 2004).

The similarity function is the complementary concept to a distance function (Ontañón, 2020). This means that, the cases that are similar must have less distance (Richter and Weber, 2016). In the literature, a variety of distance functions are available to measure the similarity between the cases. The most common distance function used is the Euclidean Distance function, which is formulated as (8):

$$E(nc_i, pc_i) = \sqrt{\sum_{i=1}^m (nc_i, pc_i)^2} \quad (8)$$

where:

- nc and pc represent respectively the new and previous cases.
- nc_i and pc_i are respectively the i th features of nc and pc .
- m is the number of features.

An alternative function to the Euclidean Distance function is the city-block or Manhattan Distance function that requires less computation and is defined as (9) (Wilson):

$$M(nc_i, pc_i) = \sum_{i=1}^m |nc_i - pc_i| \quad (9)$$

The Minkowski Distance function is the generalized function of Euclidean and Manhattan Distance, where $r = 1$ and 2 Manhattan Distance and Euclidean Distance respectively. It is defined as (10):

$$D(nc_i, pc_i) = \left(\sum_{i=1}^m |nc_i - pc_i|^r \right)^{1/r} \quad (10)$$

According to the comparison study published by Núñez et al. (2004), the different similarity measures have a performance strongly related to the type of attributes representing the case. The Euclidean distance is more appropriate for continuous quantitative values (Feuillâtre et al., 2020). However, it is very difficult to deal with ordered discrete data or non-ordered discrete data. Therefore, Wilson and Martinez (1997) proposed an efficient solution which is the Heterogeneous Value Difference Metric (HVDM). This latter combined the benefits of the Euclidean distance for and Value Difference Metric (VDM), introduced by Stanfill and Waltz (1986), for the quantitative and nominal attributes respectively. Thus, we use the HVDM to measure the similarity between the new and the previous cases. It is defined as (11):

$$HVDM(nc_i, pc_i) = \sqrt{\sum_{i=1}^m d_i^2(nc_i, pc_i)} \quad (11)$$

Where:

- m is the number of attributes.
- $d_i(nc_i, pc_i)$ is a function that returns a distance between the two values nc_i and pc_i for attribute i , and is defined as (12):

$$d_i(nc_i, pc_i) = \begin{cases} 1, & \text{if } nc_i \text{ and } pc_i \text{ is unknown;} \\ & \text{otherwise.} \\ \text{normalized_vdm}_i(nc_i, pc_i), & \text{if } i \text{ is} \\ \text{nominal.} \\ \text{normalized_diff}_i(nc_i, pc_i), & \text{if } i \text{ is} \\ \text{linear.} \end{cases} \quad (12)$$

With:

$$\text{normalized_vdm}_i(nc_i, pc_i) = \sqrt{\sum_{j=1}^c \left| \frac{N_{i,nc_i,j}}{N_{i,nc_i}} - \frac{N_{i,pc_i,j}}{N_{i,nc_i}} \right|^2}$$

Where:

- $N_{i,nc_i,j}$ is the number of instances that have value nc_i for attribute i and output class j .
- N_{i,nc_i} the number of instances that have value nc_i for attribute i .
- c is the number of output classes in the problem domain.

$$\text{normalized_diff}_i(nc_i, pc_i) = \frac{|nc_i - pc_i|}{4\sigma_i}$$

Where:

- σ_i is the standard deviation of the numeric values of attribute i .

4. AN APPLICATION EXAMPLE

In this part, we present an example of the representation of cases for new urgent request scenario with a single caregiver. After the planned route has been initiated, a new urgent request appears with the following information: CI = 2, CL = (17,35), QC = nurse, Gender = female, L = {2,3,4}, PID = 8, GIR = 3, TW = [10 AM, 11 AM], PR = female, GI=(20,40), service requested = injection, number of caregivers required to the service = 1, duration of the service = 5 min.

Thus, this request results in detecting a new problem which needs to be solved by adding it to the current routes between patients 1 and 2, as shown in figure 3. Therefore, the information of this perturbation can be represented as follow:

- Representation of the CI vector:
 $CI = \langle CID = 2; QC = 3; CL = (17, 35);$
 $Gender = 1; GIR_{list} = \{3, 4\}; L = \{2, 3, 4\} \rangle$
- Representation of the PI vector:

$$PI = \langle PID = 8; GIR = 3; TW = [10AM, 11AM];$$

$$PR = 1; GL = (20, 40) \rangle$$

- Representation of SI vector:

$$SI = \langle s_{type} = 3; s_{degree}; l_{require_caregiver} = 1;$$

$$s_{duration} = 5min \rangle$$

- Representation of TP vector:

$$TP = \langle 1; 0; 0; 0 \rangle$$

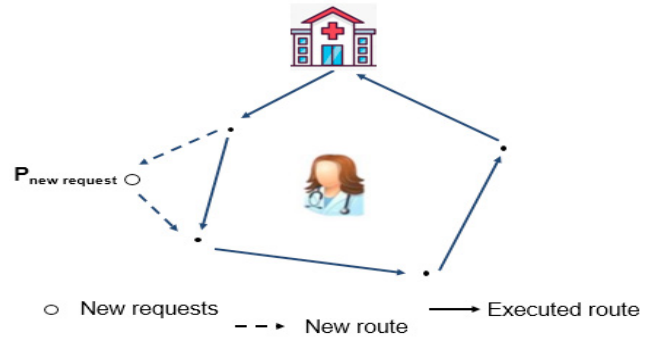


Fig. 3. Illustration of scenario 1

5. CONCLUSION

The HHC routing and scheduling problem considering the unexpected events has become recently a major challenge for the HHC companies. The challenge is to design a robust decision support system for the online daily routing plan for caregivers in order to reduce the delay of caregivers arriving at the patients' homes.

The majority of existing studies suggest metaheuristics methods for the online HHC planning in which they cannot react instantly to the perturbation (i.e. when an unexpected event occurs, the initial schedule will be updated by re-optimizing the schedule parameters with the new information). In this paper, we suggested a reactive strategy based on CBR methodology to solve the problem. We proposed creating the HHC case base by presenting the structure of cases in the HHC planning context. In our future work, we will aim at implementing and testing the proposed approach. Additionally, we will aim for merging the CBR with other artificial intelligence techniques in order to improve the quality of solutions.

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