A Recommender System Based on Multi Agent System for Real Time Home Health Care Scheduling

Mouhamed Aziz Souissi[1] and Houyem Ben Hassen[2] and Jihene Tounsi[3]

***Abstract*— Home Health Care (HHC) has become an alternative option to traditional hospitalization, especially during the COVID-19 pandemic, and aims to help people with disabilities and improve their quality of life while reducing the burden on hospital resources. The main challenge for HHC companies is to assign the appropriate caregivers to patients and schedule HHC services on an optimized route. However, the HHC schedule can be affected by unexpected events such as cancelled services, emergencies requiring care, or medical device problems. These unexpected events can cause conflict in the HHC schedule. Taking these events into account, this paper focuses on the real-time scheduling and routing problems of HHC. The proposed solution integrates the power of a multi-agent system and a recommendation system to effectively assign and schedule caregivers' care visits in real time by handling unexpected events. Patient assignment is achieved through a combination of filtering systems, clustering algorithms, and the Nearest Neighbor (NN) algorithm. Computational results highlight the efficiency of the proposed solution in terms of CPU running times.**

I. INTRODUCTION

In recent years, Home Health Care (HHC) has grown rapidly in multiple countries around the world, especially in Europe and north American countries [1]. The aging of population, the increase of people with chronic diseases and the emergence of pandemic diseases like COVID-19 are the causes of this significant growth [2].

HHC offer medical services to disabled people or people that need assistance in their daily life at their home. The HHC services may include medical services, and living assistance services. The HHC services is less expensive and often more convenient for patients with chronic diseases without being admit to the hospital for each treatment [4]. The main challenges of HHC companies is to assign caregivers to patients, and scheduling routes and times for services.

In this paper, we propose a home health care scheduling solution dealing with patients and caregivers availabilities, caregivers qualification, caregivers break and unexpected events (e.g. cancelled services, emergencies requiring care, or medical device problems) that may occur and disrupt the caregivers routes. In this context, we are using advances in artificial intelligence to develop a decentralized solution that generates data-driven decisions. Our contribution merges the multi-agent paradigm with the advantages of recommendation systems and learning algorithms (clustering algorithms and Nearest Neighbor algorithm).

The rest of the paper is structured as follows: Section II provides an overview of the literature concerning HHC scheduling problem. Section III outlines the proposed solution. Section IV delves into experimental results. And, Section V is dedicated to conclusions and future directions.

*This work was not supported by any organization

[1]SMART LAB, University of Tunis, Tunisia souissimouhamedaziz99@gmail.com

[2]SMART LAB, University of Tunis, Tunisia houyem.benhassenn@gmail.com

[3]SMART LAB, University of Tunis, IHEC, University of Carthage, Tunisia jihene.tounsi@ihec.ucar.tn

II. LITERATURE REVIEW

The HHC organization involves assignment problems, partitioning problem and routing and scheduling problems [3]. The HHC scheduling and routing problem have attracted the attention of a large number of researchers in recent years [18]. This section provides a comprehensive review of the relevant literature and existing approaches related to home healthcare scheduling and routing problem.

A. Home care routing and scheduling problem

In literature, Scheduling tasks known as Home Health Care Routing and Scheduling Problems (HHCRSP) [4]. HHCRSP aims to assign health care services to skilled caregivers, plan patient visit times, and design caregiver routes while respecting various constraints (e.g. caregivers qualification, time windows, etc) [15]. Recent studies published by [16], [17], [15] have reviewed the different objectives and constraints considered as well as the various suggested solution to solve the HHCRSP. This paper focuses on reviewing recent studies of HHCRSP considering the unexpected events.

Recently, [5] suggests a Case-Based Reasoning methodology to solve the HHCRSP considering the unexpected events. The authors introduce a HHC case base that includes the knowledge about each perturbation occur the caregiver routes during the day. More recently, [4] introduces an exact two-phase approach for re-optimizing home care routes. The first phase involves constructing initial routes for caregivers based on the required services and constraints and in the second phase, the routes are re-optimized to enhance the routing efficiency by considering dynamic changes in patient demands and caregiver availability.

B. Multi-Agent System

In recent years, Multi-Agent Systems (MAS) have attracted significant interest, particularly in home health care for addressing transport planning and scheduling challenges. MAS are composed of autonomous agents—either software or human entities—that can act independently, control their internal states, and proactively pursue their objectives [6].

These agents are capable of learning from experience and interacting socially, either cooperatively or competitively. MAS facilitate parallel processing, efficient workload distribution, and enhanced robustness through inter-agent collaboration and information sharing, making it easier to manage and scale complex tasks as the number of agents increases.

Agents are categorized as cognitive or reactive [6].

- **Reactive agents:** Agents that respond directly to the current environment using simple rules, without referencing past or future states.
- **Cognitive agents:** Agents with human-like cognitive abilities for reasoning and learning, capable of communication and executing explicit strategies.

In the existing HHC literature, some other studies have used the MAS to solve the HHCRSP. For instance, [7] provides a new way of solving a large caregiver routing problem using the caregiver's ability to dynamically design his own route while respecting four decision making rules. The aim of their work is to solve the routing problem in a dynamic context using a Multi-Agent System. Also, [8] have developed a dynamic and responsive scheduling solution that can quickly adapt to changing conditions and new orders.

C. Recommender System

With the rapid growth of online information, recommender systems have become essential for mitigating information overload by identifying and suggesting relevant items to users [9]. These systems leverage user profiles and historical data to provide personalized recommendations, aiming to present the most pertinent information and services. Recommender systems can be classified according to the type of information used to generate suggestions.

Recommender systems are classified according to the information used for generating recommendations [9].

- **Content-based filtering:** Recommends items similar to those a user previously liked, using item attributes.
- **Collaborative filtering:** Predicts preferences by analyzing interactions between users and items.
- **Demographic filtering:** Suggests items based on user demographics (age, location, etc.).
- **Knowledge-based:** Used for rarely purchased items, relying on explicit domain knowledge.
- **Hybrid systems:** Combine methods to improve robustness and accuracy.

The recommender system have been applied in different other fields, such as in tourism [11], [12]. To the best of our knowledge, the recommender system has not been applied in the HHCRSP field.

D. Contribution of this work

Table I summarizes some recent studies dealing with the unexpected events to solve the HHCRSP. Our contribution merges the multi-agent paradigm with the advantages of recommendation systems and learning algorithms. The decision to utilize a multi-agent system (MAS) alongside a recommender system stems from the inherent complexities of the dynamic environment and the decentralized nature of the task at hand. Given the diverse and evolving needs of patients, along with the fluctuating availability of resources and caregivers, a traditional centralized approach would be inadequate. By employing a MAS, we empower individual agents to autonomously assess situational factors, such as patient conditions, caregiver skill sets, and real-time logistical constraints, enabling them to collaboratively generate optimal routing and scheduling solutions. Additionally, the integration of a recommender system enhances this process by leveraging past data and user preferences to provide personalized recommendations, thereby improving the overall efficiency and effectiveness of the home health care delivery process. Together, the MAS and recommender system offer a robust framework capable of addressing the dynamic challenges inherent in home health care routing and scheduling while maintaining a decentralized decision-making approach. Furthermore, several constraints have taken into account in our study are: Time Window (TW), Working Time (WT), Preference (PR), Lunch Break (BR), Geo-location (GE), Real Time Scheduling (RT), GIR index (which is a score derived from the AGGIR grid to evaluate patients' dependency levels).

III. Proposed solution

In this section, we present our proposed approach, which encompasses three core components: a conceptual model, agents interactions, and a recommender system. Each of these components plays a crucial role in the overall framework, contributing to a robust and efficient solution

A. Conceptual model

To assist caregivers in making informed decisions during the scheduling process in a dynamic environment, while facilitating effective communication among various stakeholders, our approach leverages Multi-Agent Systems (MAS). The first step in implementing this methodology involves identifying the reasoning capabilities of each agent. The system comprises two categories of agent architectures: cognitive agents and reactive agents, as illustrated in Figure 1 and detailed in Table II, which outlines the characteristics of each actor in the system.

Our system is based on a fully decentralized multi-agent architecture, where each caregiver agent is associated with its own recommender system agent and interacts in real time with a patient agent. Unlike centralized systems, where a single entity handles assignments, our approach enables each caregiver agent to make independent decisions using data retrieved from a central server. The recommender system employs localized selection algorithms to identify the most suitable patient based on various constraints, including location, skills, and availability. Once a patient is assigned, the corresponding patient agent is immediately notified, ensuring real-time adaptability. Moreover, agents exchange updates regarding patient status, thus supporting a dynamic and reactive scheduling system.

The scheduling process represents the core of our methodology. A recommender system is used to match caregivers

TABLE I

OBJECTIVES, CONSTRAINTS AND SOLUTION METHODS OF THE REVIEWED PAPERS

Authors	Objectives	Constraints	Solution Method
[10]	minimize the travel cost of the caregiver	TW, QU, PR, GE	A combination of Multi Agent System, AnyLogic-based simulation model and iterative bidding framework
[7]	minimize the total traveling distance, minimize the waiting time	QU, TW, GE, WT	A new approach based on Multi Agent System while respecting four decision making rules.
[8]	enhance the quality and confidence of scheduling compositions, support group decision-making and improve the overall scheduling process	TW	A combination of a swarm approach, Multi-Agent Systems (MAS), and optimization methods.
[14]	minimize the total distance cost and minimize the violation of time window while maximizing patient satisfaction	TW, QU, WT, GE, PR, BK	A combination between Multi Agent System and Artificial Immune Algorithm (AIS).
[5]	reduce caregivers' delays in arriving at patients' homes while maximizing patients' satisfaction	QU, TW, PR, GIR, GE, WT, BK	A dynamic approach with consideration of the unexpected events using a Case-Based Reasoning (CBR) methodology.
[13]	minimizes the Total Planning Distance (TPD) and maximize the total caregiver-patient compatibility	TW, QU, PR	A matheuristic-based algorithm using a Mixed-Integer Programming (MIP) approach
[4]	Minimization of the amplitude of a day and perceived waiting times	TW, QU, WT, BK	An innovative exact approach based on a modelization of the problem with graphs.
This paper	minimize response time and minimize the travel distance while respecting all constraints	TW, QU, WT, BK, GE, PR, GIR and RT	Real time scheduling based on MAS, Recommender System and Clustering algorithm.

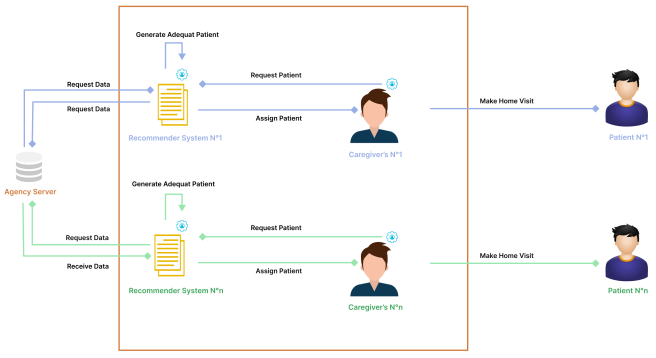

Fig. 1. Proposed system architecture based on MAS

TABLE II

AGENT BEHAVIORS

Actors	Type of agent	Description
Caregiver	Reactive Agent	Passive Behavior: He visits his patients according to the planned route provided by the recommender system. • He sends patient requests.
Recommender System	Cognitive Agent	Active Behavior: He receives request from caregiver then affect adequate patient to caregiver according to their qualifications, preferences, time window, etc.

with patients while considering multiple constraints. Once assignments are completed, caregivers proceed with planned home visits. However, if unexpected events occur or a patient's condition changes, the system dynamically adapts by rescheduling and reassigning caregivers based on the updated patient status. At this stage, various factors, such as caregiver qualifications and working hours, are factored into the decision-making process.An overview of our MAS-based framework is presented in Figure 1.

B. Agent's Interaction

As illustrated in Figure 2, our system follows a decentralized multi-agent approach, where each caregiver agent operates alongside its own recommender system agent. The interaction begins when a caregiver agent initiates a treatment request by sending a Call for Request (CFR) to its assigned recommender system agent.

Upon receiving the CFR, the recommender system agent first verifies the caregiver's working hours and availability. If unavailable, the agent immediately notifies the caregiver. Otherwise, the agent retrieves a filtered list of potential patients and applies its local selection algorithm to determine the most suitable match based on multiple constraints, such as time windows, caregiver qualifications, preferences, and the patient's gender-inclusive risk index score.

Unlike centralized systems, where assignments are dictated by a single decision-making entity, each recommender system agent operates fully autonomously, making real-time patient assignments without requiring external validation. This autonomy allows the system to be more scalable, reactive, and adaptable to real-time events. If a caregiver becomes unavailable or a patient's condition changes after assignment, the system dynamically reassigns patients based on updated constraints, ensuring continuous and efficient scheduling.

C. Recommender system

The proposed system assists caregivers in obtaining optimal patient matches for their treatment needs. To address

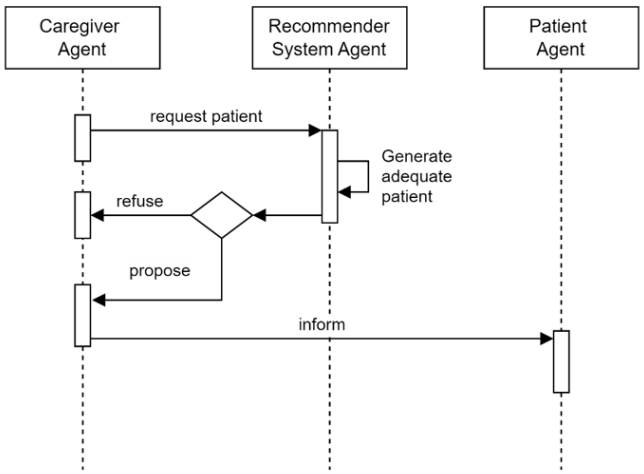

Fig. 2. Agents interaction based on sequence diagram

concerns about the alignment with a true recommender system, our approach is detailed as follows:

Our recommendation system combines content-based filtering and demographic filtering to optimize patient-caregiver assignments. It considers key criteria such as caregiver qualifications, time constraints, and patient needs. The algorithm first clusters patients based on geolocation using k-means, which effectively segments patients into groups with similar geographic proximity. This is followed by applying a Nearest Neighbor (NN) algorithm to find the best match within each cluster. This comprehensive approach improves the accuracy and efficiency of assignments by considering multiple constraints, such as caregiver skills, patient preferences, and time availability, ensuring a more effective scheduling process.

For optimal operation, the system involves three key stages:

- Collect detailed information about the caregiver's qualifications, preferences, and time constraints through content-based filtering.
- Select potential patients that match the caregiver's criteria using demographic filtering to refine patient lists.
- Execute a hybrid approach with k-means clustering followed by the Nearest Neighbor (NN) algorithm for precise patient matching.

The scenario involves five steps that are described as follows:

1) The caregiver specifies his actual location.
2) From the Patients database, the system selects a refined list of patients according to the criteria selected by the caregiver.
3) Geolocalisation of Patients is a key step before the clustering process. Hence, Google Maps service is used to obtain places coordinates.
4) The patient generation component integrates the implemented algorithm that begins by grouping the Patients into clusters according to their localization. Then, it solves the problem by matching caregiver with an adequate patient.
5) The suggested patient is displayed by the viewer on a map showing the suggested location of the patient

Figure 3 shows the proposed architecture framework designed for the HHC scheduling. It provides an in-depth overview of the various modules. Subsection III-C.1 discusses the caregiver information module, which contains details about the caregivers. Subsection III-C.2 examines the data retrieval module, which obtain the necessary data. Subsection III-C.3 presents the module for generating suitable patient recommendations based on the inputs from the previous modules. Through the integration of these different modules, the proposed framework aims to optimize the patient assignment process and reduce the time spent on scheduling and routing tasks. Specifically, these modules work to efficiently match patients with caregivers based on their respective preferences and constraints.

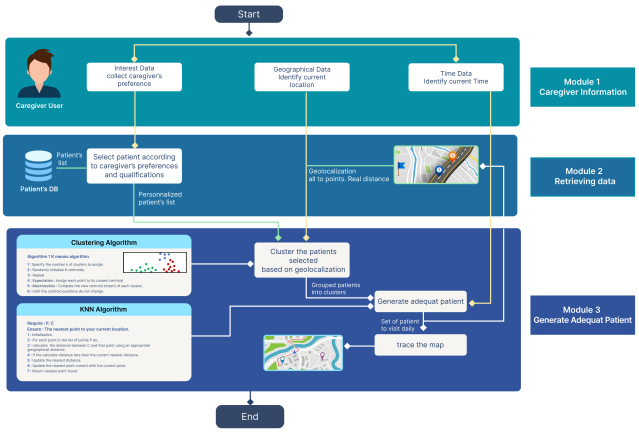

Fig. 3. The proposed architecture of the scheduling solution

1) Caregiver information: Our system allows caregivers to effortlessly provide their information and set their preferences. Through the user interface, caregivers can enter demographic data, including their name, age, and more. Additionally, they have the option to select their preferences, qualifications, and areas of interest from a predetermined list. Furthermore, caregivers are required to specify their current location.

2) Data retrieving: To effectively filter and retrieve the data, we implemented a robust and efficient system tailored to our specific needs. The process began by identifying the key criteria for filtering. First, we filtered the list of patients based on gender, selecting only those who matched the specified gender criteria.Next, we refined the list further by including only the patients whose service requests matched the qualifications of the caregiver. We then verified that the remaining patients had a GIR index that corresponded to the caregiver's requirements. Finally, we ensured that the patients had a visit date within the time window when the caregiver sent the request.

3) Generation of adequate patient: The main contribution of our research is the development of an efficient service

based on metaheuristics in real time. Once we have our personalized list of patients that match all criteria of caregiver, two steps are considered for the generation service.

a) Clustering: In this step, our objective is to group list of patients generated and caregiver based on their locations into clusters. To accomplish this, we employ the k-means algorithm. K-means algorithm is a highly effective clustering algorithm that is commonly utilized for solving routing problems. Its fundamental concept involves acquiring k centroids, where each centroid represents a cluster. The input for this algorithm consists of the geographical coordinates of patients, while the number of clusters is determined by using the silhouette score method. To obtain the localization points, we extract data from Google Maps.

b) Generation of Nearest Patients Using NN: This step involves working within the designated cluster. Our system suggests the best-suited patient to the caregiver while considering multiple constraints (e.g. Time Windows, Preferences, Qualification, GeoLocation and Real Time). The main goal is to reduce the distance the caregiver needs to travel to reach the patient. The algorithm 1 shows the pseudo-code of the nearest neighbor algorithm. In the pseudo-code, P represents the list of patients that were clustered together, C is the current location of the caregiver, and D corresponds to the distance covered by the caregiver C until they reach the patient i.

Algorithm 1 Nearest Neighbor Algorithm

Require: P, C
Ensure: The nearest
Initialisation

for each point p in P **do**
  Calculate distance between C and that point using an appropriate geographical distance.
  if *calculated distance* is less than *current nearest distance* **then**
    Update *nearest distance*
    Update *nearest point with the current point.*
  end if
end for

IV. Experimental Results

The objective of our experiments is to evaluate the effectiveness of the proposed recommendation system in optimizing the allocation of caregivers to patients while considering real-time constraints. This section presents the experimental setup, the methods evaluated, and the results obtained from our approach.

A. Experimental Setup

To simulate realistic scenarios, we used synthetic data generated by an AI-based tool[1] developed with Ruby. This dataset comprises information on 1000 patients and 30 caregivers. Tables III and IV detail the attributes used for patients and caregivers respectively.

TABLE III
Patient Information

Patient ID	Gender	Service Request	Time Windows	GIR Index	Lat	Long
Pat1	Male	Nursing	2023-09-17 09:00:00	2	37.682	10.881
Pat2	Female	Blood Monitoring	2023-09-17 13:00:00	1	37.119	10.728
Pat3	Male	Home Physiotherapy	2023-09-17 17:00:00	3	36.369	10.814
Pat4	Male	Blood Monitoring	2023-09-18 10:00:00	2	37.679	10.600
Pat5	Female	Home Aides	2023-09-17 14:30:00	4	37.700	10.635

TABLE IV
Caregiver Information

Caregiver ID	Gender	Qualification	Working Time	GIR Index	Lat	Long
Caregiver1	Male	Nurse	6	[1, 2]	37.682	10.881
Caregiver2	Female	Physiotherapist	4	[1]	37.119	10.728
Caregiver3	Male	Speech Therapist	8	[1, 3]	36.369	10.814
Caregiver4	Male	Auxiliary Nurse	2	[4]	37.679	10.600
Caregiver5	Female	Speech Therapist	7	[1, 4]	37.700	10.635

B. Clustering Method Evaluation

To optimize caregiver-patient allocation based on geographical clustering, we evaluated various clustering algorithms: K-means, DBSCAN, Hierarchical Clustering, and MeanShift. Performance was assessed using the silhouette score to determine the coherence within clusters. Table V summarizes the comparative results, indicating that the K-means algorithm achieved the highest silhouette score of 0.51321. Thus, K-means became the algorithm of choice for further analysis, using 3 clusters as the optimal configuration.

TABLE V
Comparison of Clustering Algorithms

	Clustering Algorithms			
	K-means	Hierarchical Clustering	DBSCAN	MeanShift
Number of Clusters	3	10	3	6
Silhouette Score	0.51321	0.41244	0.46203	0.38236

[1]https://www.mockaroo.com

C. Scheduling Optimization Analysis

Table VI presents the results of our scheduling solution. The experiments were designed to determine the system's efficiency in scheduling patient visits. Metrics such as the number of patients visited and computational time were analyzed, demonstrating the practicality of the proposed approach.

TABLE VI
EXPERIMENTAL RESULTS OF SCHEDULING SOLUTION

Number of Caregivers	Number of Patients	Number of Patients Visited	Patients Visited After 18:00	Scheduling Time (sec)
5	10	4	0	1
	50	12	0	1
	100	19	0	1
	500	42	4	2
15	10	6	0	1
	50	21	0	1
	100	47	1	1
	500	121	8	2
30	10	7	0	1
	50	39	2	1
	100	69	0	1
	500	200	11	2

D. Results and Discussion

Analysis demonstrates that combining K-means clustering with Nearest Neighbor routing minimizes travel distance and response time compared to traditional methods, while maintaining efficient service delivery and low computational demand.

Through our detailed experimental assessment, we validate the system's capability to optimize healthcare operations dynamically, offering both efficiency and high levels of satisfaction for all parties involved.

V. CONCLUSIONS

This paper introduces a multi-agent model designed to solve the Home Health Care Routing and Scheduling Problem (HHCRSP), with the goal of minimizing overall travel distances and costs while enhancing patient satisfaction. A recommender system dynamically matches each caregiver with the most suitable patient in real-time, considering constraints such as time windows, qualifications, preferences, GIR index, and geolocations. Our system combines content-based and demographic recommendations, accommodating unexpected events like staff unavailability or caregiver absences.

The proposed approach involves three main steps: collecting caregiver information, generating a list of patients that meet all constraints, and performing clustering based on geographic proximity. The Nearest Neighbor algorithm is then applied to identify the closest patient for each caregiver.

As future work, we will investigate advanced synchronization and dynamic resource allocation to improve caregiver coordination and optimize assignments in real time. We also plan to study shared-care scenarios involving multiple caregivers per task, and to rigorously evaluate system scalability under high-load and resource contention conditions to ensure robust deployment.

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