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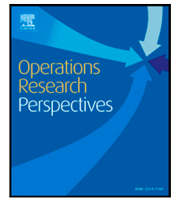
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A multiobjective approach for weekly Green Home Health Care routing and scheduling problem with care continuity and synchronized services

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ABSTRACT

Home Health Care (HHC) services are essential for delivering healthcare programs to patients in their homes, with the goal of reducing hospitalization rates and improving patients' quality of life. However, HHC organizations face significant challenges in scheduling and routing caregivers for home care visits due to complex criteria and constraints. This paper addresses these challenges by considering both caregiver assignments and transportation logistics. The objective is to minimize the total travel distance and CO₂ emissions while ensuring a balanced workload for caregivers, meeting patients' preferences, synchronization, precedence, and availability constraints. To tackle this problem, we propose a multiperiodic Green Home Health Care (GHHC) framework. In the first stage, we utilize multiobjective programming and the NSGA-II algorithm to generate Pareto front solutions that consider travel distance and CO₂ emissions. In the second stage, a Mixed-Integer Linear Programming (MILP) model is proposed to balance caregivers' workload by assigning them to the patient routes generated in the first stage. The results highlight the trade-off between shorter routes and lower emissions. Furthermore, we examine the impact of prioritizing continuity of care and patient satisfaction. This research provides valuable insights into addressing the scheduling and routing challenges in HHC services, contributing to a more efficient and environmentally friendly healthcare delivery.

1. Introduction

Home Health Care (HHC) services encompass a wide range of healthcare programs provided to patients in their own homes [1,2]. On a daily basis, HHC organizations receive numerous requests from new patients seeking home-based treatment, necessitating strategic preparations for caregiver management. The HHC problem is a well-known challenge in workforce scheduling and routing [3].

Due to the escalating expenses associated with hospital procedures, primary care has been compelled to offer nursing services at patients' homes to minimize costs. HHC services aim to reduce hospitalization rates and alleviate the burden on healthcare facilities [4,5]. These services enhance the quality of life for patients, particularly those requiring support and specialized medical care. Reports from the World Health Organization (WHO) also indicate that elderly patients prefer informal care in their homes rather than formal care in hospitals [6]. In HHC organizations, the scheduling of home care visits is typically done manually, resulting in prolonged planning times and additional expenses [7].

The HHC problem involves a set of patients who require care from caregivers based on their specific treatment needs. Skilled caregivers deliver care using various means of transportation, such as hospital vehicles, buses, or cars. Consequently, the HHC routing and scheduling challenge encompasses two primary operational problems: the General Assignment Problem (GAP) and the Vehicle Routing Problem (VRP).

The problem involves scheduling patients based on their requests and the specific expertise needed from caregivers. Patients may have individual preferences regarding their caregivers, including factors like gender, language, and other relevant considerations [8]. Hence, the caregiver assignment process ensures that patients' preferences are respected while considering the caregivers' skills. Another important constraint to consider is the availability of patients throughout the day, which necessitates visits to be scheduled within specific time windows.

HHC agencies often rely on transportation to ensure the delivery of care. The primary objective of transportation logistics is to establish cost-effective routes for vehicle movement. However, the combustion engines used in transportation produce a significant amount of CO₂,

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which directly impacts air quality, particularly in large cities [9]. The transportation industry is a major contributor to greenhouse gas (GHG) emissions on a global scale [10–12]. According to the International Energy Agency (IEA) [13], the transportation sector is responsible for approximately 23% of global carbon dioxide (CO₂) emissions [14]. Environmental consciousness aims to mitigate the impact of toxic emissions on the climate and calls for governments and companies to address this issue seriously [9]. Many companies and organizations have committed to adopting practices that actively reduce the amount of CO₂ emitted.

On one hand, transport firms have begun taking significant steps to reduce CO₂ emissions for various purposes. On the other hand, governments encourage the use of environmentally friendly vehicles to achieve the same goal [12].

This study considers the problem in a multiperiodic context, where each period represents a day. Daily planning involves designing routes to provide treatment to patients who require multiple care sessions per day, assigning them to suitable caregivers. The daily problem is a bi-objective one, aiming to minimize both the total travel distance and CO₂ emissions. This problem, known as the Green Vehicle Routing Problem (GVRP), takes into account several constraints and criteria related to HHC routing and scheduling. These include balancing caregivers' workload, minimizing caregivers' travel distance, reducing CO₂ emissions, considering the affinity between the patient and caregiver, aligning patients' needs with caregivers' skills, considering patients' availability within specific time windows, addressing the temporal dependency of care sessions, managing precedence constraints, ensuring synchronization between caregivers, maintaining continuity of care, and respecting caregivers' maximum daily workload. As noted by Cissé et al. [8], there are no available instance sets for explicit comparison of HHC models and approaches. Therefore, we implemented the standard Nondominated Sorting Genetic Algorithm II (NSGA-II) and different NSGA-II-based methods to generate Pareto front solutions using well-known Traveling Salesman Problem (TSP) benchmarks [15], adapted with specific HHC data. Our results indicate that shorter routes do not always lead to lower CO₂ emissions.

Our proposed approach consists of two stages: The first stage involves a multiobjective programming model that minimizes both the total travel distance and CO₂ emissions using different versions of the NSGA-II algorithm. In the second stage, we introduce a Mixed-Integer Linear Programming (MILP) model that aims to balance the workload of caregivers by assigning them to the designed patient routes from the first-stage model. We also consider scenarios where continuity of care is not prioritized in the planning process and compare the approach in terms of objective functions, computation time, and patient and caregiver satisfaction.

The remainder of this paper is organized as follows: Section 2 provides an overview of current research on HHC scheduling and routing problems. Section 3 discusses green logistics and transportation concepts, along with methods for measuring CO₂ emissions. Section 4 describes the problem under study, including mathematical models and formulations. Section 5 presents the solution approach, NSGA-II operators, and local search procedures. Section 6 presents computational results, utilizing various performance metrics to evaluate the proposed approach. Section 7 conducts a sensitivity analysis, and Section 8 offers managerial insights for HHC organizations. Finally, Section 9 concludes the paper and provides insights for future work.

2. Literature review

In recent years, the HHC problem has attracted considerable attention in recent years due to its importance in optimizing the capacity of clinics, nursing homes, and medical personnel while alleviating the burden on hospitals and clinics [16]. HHC organizations play a crucial role in providing healthcare services and reducing the strain on health

care facilities [16]. Heching et al. [17] presented a Logic-Based Benders Decomposition (LBD) as an exact optimization method for HHC delivery, showcasing its superiority over mixed integer programming in efficiently matching patients with healthcare aides and scheduling their home visits.

The planning process for HHC is typically divided into three decision levels: long-term strategic, medium-term tactical, and short-term operational [18,19]. At the strategic level, the focus is on districting, which involves dividing the HHC service area into clusters of patients and assigning these clusters to specific resources [8,18]. The strategic level encompasses three main problems: partitioning, assignment, and classification [20–22]. The tactical level, influenced by strategic decisions, involves determining the number of caregivers and dimensioning the necessary resources, which can be personnel or materials [8,23]. Finally, the operational level deals with the assignment of caregivers to patients and the scheduling of appointments. It encompasses routing and scheduling problems based on decisions made at the strategic and tactical levels. For an extensive literature review on HHC planning and scheduling, refer to Benzarti et al. [24], Di Mascolo et al. [25], Fikar and Hirsch [26], Cissé et al. [8], Grieco et al. [27], Di Mascolo et al. [28], Chabouh et al. [29] and Goodarzi et al. [30]. In this study, our focus is primarily on the literature related to the operational level of HHC planning and scheduling.

The operational level primarily involves addressing the caregivers' assignment problem and the HHC routing and scheduling problem. The caregivers' assignment problem revolves around determining which caregiver should be assigned to each patient, while the HHC routing and scheduling problem focuses on efficiently scheduling patient appointments for each caregiver. These two problems can be tackled together or separately [8].

Several factors contribute to the complexity of the HHC routing and scheduling problem [26]. One such factor is the continuity of care, which limits the number of caregivers assigned to a patient during a planning horizon. When a patient is assigned to a specific caregiver throughout the planning horizon, it is known as full continuity of care [8]. Continuity of care is a crucial criterion as it helps build confidence between caregivers and patients. However, due to patients' varying needs, achieving full continuity of care may not always be feasible. Therefore, researchers strive to minimize the number of assigned caregivers whenever possible [31]. Synchronization, caregivers' skills, and patient preferences are also critical criteria in the HHC routing and scheduling problem.

The VRP is one of the most well-known and extensively studied NP-hard problems in operations research [32–34]. It involves a fleet of vehicles serving a set of customers, with the goal of minimizing costs associated with travel distance, number of vehicles used, etc. The routing problem in HHC is a variant of the VRP, incorporating unique constraints and criteria specific to HHC settings [8]. The GVRP, introduced by Erdoğan and Miller-Hooks [35], specifically focuses on minimizing Greenhouse Gas (GHG) emissions. For a comprehensive review of the green routing problem, refer to Marrekchi et al. [36]. In 2014, El Bouzekri El Idrissi and El Hilali Alaoui [37] proposed a bi-objective GVRP that aims to minimize both total travel distance and carbon dioxide emissions. They solved the problem using a genetic algorithm. Additionally, El Bouzekri El Idrissi et al. [38] developed a technique to estimate carbon dioxide emissions for the capacitated VRP and used a genetic algorithm to solve it. Messaoud et al. [39] combined the dynamic VRP with the GVRP to minimize carbon dioxide emissions, employing an Ant Colony Optimization (ACO) algorithm hybridized with a large neighborhood search. Zhang et al. [40] addressed the capacitated GVRP using alternative fuel-powered vehicles, employing a two-phase heuristic algorithm and an ACO-based metaheuristic approach. Later, Shi et al. [41] proposed a robust optimization model for VRP, integrating GHG emission reduction objectives. Using a hybrid tabu search and simulated annealing approach. They highlighted the

importance of considering uncertainties, with practical applications demonstrated in logging truck routing planning.

Turning to the HHC routing and scheduling problem, Ikegami and Uno [42] proposed an approach to determine the required number of caregivers, considering maximum service limits, continuity of care, and time window constraints. Kergosien et al. [43] presented a MILP model, extending the multiple Traveling Salesman with Time Window Problem (mTSTWP) to HHC. They aimed to minimize travel time costs while incorporating HHC-specific constraints, such as patient availability, caregiver expertise, care preferences, and synchronization. Nickel et al. [44] introduced a multiperiod model for HHC, solving it using metaheuristics combined with constraint programming methods. Kergosien et al. [45] developed an Integer Linear Programming (ILP) model for blood sample collections in HHC, considering constraints like blood sample expiration time, patient preferences, and delays. They used various metaheuristics to solve the problem and select the best solution. The experimental study utilizes real data from a Canadian health center. Bard et al. [46] proposed a MILP model for the HHC routing and scheduling problem and developed an adaptive sequential greedy randomized adaptive search procedure. Their model incorporated preferences, patient and caregiver time windows, overtime, holidays, workload balancing, and other factors. Wornitzer et al. [31] presented a mid-term HHC approach using five MIP formulations with different continuity measures. Grenouilleau et al. [6] developed a method based on set partitioning formulation and a large neighborhood search framework. The problem was solved using the columns generated by the large neighborhood search. Moussavi et al. [47] presented a metaheuristic approach for integrating caregivers' assignment and VRP in the context of HHC. Their approach considered multiple days, including off-days, and applied a decomposition approach to simplify the model. Belhor et al. [48] addressed the cancer treatment process through chemotherapy in the context of HHC, employing a MILP to minimize delivery time. They also utilized a machine learning method based on the genetic fuzzy system. Tanoumand and Ünlüyurt [49] proposed an approach to solve the HHC routing problem, considering consistency between patients' requirements and caregivers' skills and qualifications. They employed a branch-and-price algorithm to solve the problem.

2.1. Multiobjective home health care (HHC) problems

Multiobjective optimization models have emerged as valuable tools for balancing various conflicting objectives [50], such as minimizing operational costs, maximizing patient satisfaction, and promoting sustainable practices in HHC systems. These approaches are resolved using either exact algorithms or metaheuristics, offering novel insights and methodologies to enhance the efficiency of HHC delivery. Teresinha et al. [51] addressed the challenge of optimizing healthcare service distribution in Brazil, by proposing a partitioning model based on optimizing population homogeneity, medical procedure variety, and patient travel distance. Their approach, using a multiobjective genetic algorithm, offers significant advancements in territory districting and healthcare system optimization. Duque et al. [52] introduced a bi-objective mathematical model based on a set partitioning formulation for the HHC problem. Their model aimed to maximize services while minimizing caregivers' total travel distance, considering preferences, patient and caregiver time windows, holidays, caregivers' qualifications and skills, and continuity of care. Braekers et al. [53] proposed a bi-objective approach, aiming to balance cost efficiency with client inconvenience, shedding light on this trade-off relationship for the first time in this context. They utilized a mixed integer problem formulation enhanced with various families of valid inequalities to address the daily routing and scheduling problem. Additionally, they proposed several approaches to solve the scheduling subproblem, including a metaheuristic solution framework based on multi-directional local search. Liu et al. [54] analyzed medical team planning and

scheduling in HHC over a weekly horizon, aiming to minimize operation costs while maximizing patient satisfaction. Using a mixed integer program and ϵ -constraint method, they balanced patient requirements, medical team types, and service constraints, with heuristic approaches for large-scale instances. Decerle et al. [55] proposed a multiobjective model minimizing caregivers' total working time, maximizing service quality, and minimizing the maximum working time difference between nurses and auxiliary nurses. They solved the problem using a memetic algorithm for multiobjective optimization. Ghannadpour et al. [56] addressed the critical issue of managing medical waste generated by healthcare centers, emphasizing the importance of proper waste management to prevent environmental and health risks. They propose a sustainability-oriented routing model, termed Healthcare Waste Collection Routing Problem (HWCVRP), aiming to optimize waste transportation routes while considering economic, social, and environmental objectives. Using a multiobjective self-adaptive evolutionary algorithm, they optimize the proposed model, demonstrating its applicability through a case study on a logistics company in Iran. Fathollahi-Fard et al. [57] addressed the challenge of managing HHC operations for population aging. They established a multiobjective robust optimization model considering working-time balancing, care continuity, and uncertainties. The study innovated efficient heuristics and metaheuristics to optimize logistics cost, caregiver unemployment time, and care continuity, followed by a comprehensive comparison and sensitivity analyses for practical insights. Later, Fathollahi-Fard et al. [58] focuses in optimizing HHC logistics and services, especially during pandemics like COVID-19, to ensure efficient caregiver routing while adhering to social distancing measures. They introduce a novel triple bottom line approach for sustainable decision-making, considering economic, environmental, and social factors. Additionally, they developed a scenario-based robust optimization method to handle uncertainty and proposed an heuristic algorithm based on Lagrangian relaxation to handle multiobjective optimization. Ting et al. [59] introduced a bi-objective optimization model for the HHC problem, addressing nurse and patient preference satisfaction. Unlike previous studies, they considered patient satisfaction from the perspectives of nurse skill level and nurse-patient familiarity. Additionally, they incorporate nurses' preference satisfaction regarding overtime duration. They proposed a hybrid NSGA-II to solve the problem and demonstrate its effectiveness. Shiri et al. [60] proposed a multiobjective model for HHC, vital during events like Covid-19 outbreaks, optimizing health center opening and routing/scheduling while considering social responsibility and efficiency. Objectives include cost minimization and maximizing social responsibility. Given uncertainties, they used a robust-fuzzy approach and validated using a real case study. Bhattarai et al. [61] proposed a multiobjective framework for HHC services, utilizing a mathematical model to optimize nurse schedules, enhance service quality, and maximize provider profit in response to rising demand and costs. Oladzad-Abbasabady et al. [62] addressed the HHC routing and scheduling problem with soft and hard time windows, considering five types of soft temporal dependency constraints. They proposed a bi-objective model that aims to minimize total costs while maximizing patient satisfaction, solved using Iterated Local Search (ILS) for large-sized instances and compared to NSGA-II. Liu et al. [63] tackled the HHC routing and scheduling problem in pandemic scenarios, optimizing caregiver assignments and routes while minimizing costs and workload discrepancies. They proposed an algorithm that combines multiobjective simulated annealing with adaptive large neighborhood search, showing, efficacy in achieving trade-offs between cost reduction and workload balance while considering patient preferences.

2.2. Green Home Health Care (GHHC) problems

In the area of Green Home Health Care (GHHC), only a few papers are available in the literature. Fathollahi-Fard et al. [64] proposed

the first GHHC bi-objective optimization approach using metaheuristics and heuristics. Fathollahi-Fard et al. [12] introduced GHHC and solved the problem using a modified simulated annealing algorithm. Erdem and Koç [65] analyzed a variant of the HHC routing problem where a group of caregivers uses electric vehicles to perform a requested number of jobs. Makboul et al. [66] proposed a decomposition approach for solving the HHC routing and scheduling problem, considering numerous HHC constraints and criteria. Their approach consisted of a multiobjective problem, aiming to minimize total travel distance and fuel consumption with varying speed while balancing the workload among caregivers. Fathollahi-Fard et al. [67] considered a HHC routing and scheduling problem with greenhouse gas emissions. They proposed a bi-objective, multi-depot, and multi-period HHC approach, considering patient time windows, vehicle capacity, and the minimization of carbon emissions. They also incorporated robust optimization methods to handle uncertainty in travel and service times. Luo et al. [68] formulated a MILP and proposed a two-phase heuristic approach, combining exact methods and dynamic programming, to efficiently solve the problem. Their approach was tested on 19 instances of different scales and demonstrated effectiveness and efficiency in reducing carbon emissions while optimizing the logistics route for HHC. Goodarzian et al. [69] addressed the growing demand for private HHC for the elderly in developing countries by proposing a green HHC network. They considered uncertain conditions, time windows, and a flexible linear programming model. Two hybrid algorithms were developed and compared to find the most efficient one for real practice, and a real case study was presented to validate the proposed model. Luo et al. [70] presented an ACO-based heuristic for the HHC problem with synchronized visits and carbon emissions. They formulated the problem as a single-period VRPTW, considering constraints such as synchronization, patient time windows, and caregiver capacity, to minimize total carbon emissions. On the other hand, Luo et al. [71] proposed an exact method to solve the green HHC routing and scheduling problem using the Branch-Price-and-Cut (BPC) algorithm. Their objective was to minimize both fuel consumption costs and carbon emissions of vehicles. Finally, Garjan et al. [72] proposed a green VRP for the HHC network, designed to maximize profits while adhering to carbon dioxide emission limits and addressing environmental concerns. They presented a multi-period MILP and solved it using GAMS software, providing numerical examples to demonstrate the results and performance.

2.3. Research gaps and contributions

This study introduces a novel approach to weekly planning in HHC organizations, addressing a broad array of constraints and objectives. The main contributions include:

1. Incorporating a wide range of real-world constraints and criteria such as workload balancing, travel distance, and CO₂ emissions reduction, alongside handling precedence, synchronization, continuity of care, caregiver skill matching, patient availability, and temporal dependencies. The goal is to minimize travel distance and emissions while ensuring a balanced workload among caregivers. The NSGA-II algorithm, augmented with local search, is employed to approximate Pareto front solutions for routing and scheduling, supplemented by a MILP model to balance caregivers' workloads.
2. Proposing innovative modeling techniques tailored to synchronization constraints inherent in the problem.
3. Achieving a simultaneous reduction in travel distance and CO₂ emissions while effectively balancing workload, a feat not previously reported in the literature.
4. Developing a new coding scheme for the NSGA-II algorithm, integrating additional constraints like continuity of care, synchronization, and temporal dependencies, vehicle capacity. Additionally, a heuristic is introduced to refine individuals post-mutation. Different versions of NSGA-II, incorporating local search, are deployed and compared.

5. Analyzing the impact of various parameters and constraints including continuity of care and the number of caregivers and patients on objective functions. Additionally, sensitivity analyses on time windows and instance sizes are conducted to evaluate their effects on objective functions.
6. Demonstrating efficient computation time, even for large instances resembling real-world scenarios, making the proposed approach a valuable decision support tool for HHC services.

Table 1 presents the selected papers from the literature, focusing on investigating the periodic/mid-term HHC problem, together with the few works addressing green HHC. The comparison is based on the set of constraints and criteria: Number of objectives, number of periods, routing of caregivers, scheduling of caregivers, patient time window, preference, continuity of care, caregiver time window, qualification/skill, temporal dependency, workload balancing, uncertainty, synchronization of care, emissions, learning care, and solution algorithm. Besides, the last row in Table 1 highlights the contribution of this study. The last column presents the solution approach considered in each paper. From Table 1, we can summarize the following:

1. Few studies consider the continuity of care for long and mid-term HHC routing and scheduling problems. However, most works do not address the following constraints: synchronization of care, precedence of care, skill constraints, and learning care.
2. To the best of our knowledge, there has been no research in the literature that has achieved a simultaneous reduction in both travel distance and CO₂ emissions, while also effectively balancing workload and analyzing various parameters.
3. Studies considering synchronization are very limited [79–82].
4. Only a few studies in the literature consider the learning care in HHC problems.
5. No study considers continuity of care, time windows, synchronization of visits, gas emissions, learning care, and multiple objectives simultaneously for the multi-periodic HHC routing and scheduling problem.

3. Green transportation: Emission factors and estimates

The concept of green logistics for sustainability has gained traction in recent years due to government policies and customer demand. As mentioned earlier, skilled caregivers of HHC agencies use vehicles to provide care. The primary objective of transportation is to create cost-effective routes for vehicle movement. However, engines produce a significant amount of CO₂, which directly impacts air quality. Green logistics focuses on minimizing both route costs and CO₂ emissions generated by trucks, planes, and cars [9]. Therefore, environmentally-friendly routing has become increasingly important in many countries [36].

In this section, we present two approaches to estimate CO₂ emissions and their mathematical formulations for integration into optimization models. The fuel consumption of vehicles is influenced by several factors, including weather conditions, traffic congestion, vehicle speed, and acceleration.

3.1. Measurement of transport emissions

Making an exact estimation of CO₂ emissions is generally challenging due to several factors. However, emissions can be estimated based on factors such as the quantity of goods, speed, distance traveled, etc. We will discuss two approaches to estimate transport emissions: the distance-based method and the fuel-based approach [9].

Table 1

Comparison between the work presented in this paper and the literature.

Reference	Multiobjective	Multi-period	Routing of caregivers	Scheduling of caregivers	Patient time window	Preference	Continuity of care	Caregiver time window	Qualification/skill	Temporal dependency	Workload balancing	Uncertainty	Synchronization of care	Gas emissions	Learning care	Solution technique
Ikegami and Uno [42]	✓	✓	-	-	-	-	✓	✓	-	-	-	-	-	-	-	TS
Nickel et al. [44]	✓	✓	-	-	✓	-	-	✓	-	✓	✓	-	-	-	-	Heuristic
Liu et al. [73]	-	-	-	-	✓	-	-	-	-	✓	-	-	-	-	-	Feasible rules for TS
Bard et al. [46]	-	✓	✓	✓	✓	✓	-	✓	-	-	-	-	-	-	-	Greedy randomized adaptive search
Duque et al. [52]	✓	✓	-	-	✓	✓	✓	✓	-	✓	✓	✓	-	-	-	MIP and local search
Cappanera and Scutella [74]	-	✓	✓	✓	-	-	✓	-	✓	-	✓	-	-	-	-	ILP
Bowers et al. [75]	-	✓	✓	✓	-	✓	✓	-	-	-	✓	-	-	-	-	Clarke and Wright based heuristic and simulation
Hewitt et al. [76]	✓	✓	✓	-	-	-	✓	-	-	-	-	-	-	-	-	ConRTR algorithm
Wirmitzer et al. [31]	-	✓	-	✓	-	✓	✓	-	✓	-	-	-	-	-	-	ILP
Fikar and Hirsch [77]	-	✓	✓	✓	✓	-	-	✓	✓	-	✓	-	-	-	-	TS
Shi et al. [78]	-	-	✓	✓	✓	-	-	✓	-	-	-	✓	-	-	-	Hybrid of GA and SA
Cappanera et al. [16]	-	✓	✓	✓	✓	-	-	✓	-	-	-	✓	-	-	-	Exact
Liu et al. [54]	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-	-	-	Exact
Fathollahi-Fard et al. [64]	✓	✓	✓	✓	✓	-	-	-	-	-	-	-	-	✓	-	Heuristics, SA and SAA
Grenouilleau et al. [6]	✓	✓	-	✓	-	-	-	✓	-	-	-	-	-	-	-	Heuristics
Erdem and Koç [65]	-	-	✓	✓	✓	✓	-	-	✓	-	-	-	✓	✓(EV)	-	GA and VNS
Shi et al. [41]	-	-	✓	✓	✓	✓	-	-	-	-	-	✓	✓	✓	-	Hybrid of TS and SA
Fathollahi-Fard et al. [12]	✓	✓	✓	✓	✓	-	-	✓	-	-	-	-	-	✓	-	MSA
Fathollahi-Fard et al. [67]	✓	✓	✓	✓	✓	-	-	✓	-	-	-	✓	-	✓	-	MOKA, NSGA-II and MOPSO
Luo et al. [71]	-	-	✓	✓	✓	-	-	-	-	-	-	-	-	✓	-	BCP
Luo et al. [70]	-	-	✓	✓	✓	-	-	-	-	-	-	-	✓	✓	-	ACO-based heuristic
Fathollahi-Fard et al. [57]	✓	✓	✓	✓	✓	-	✓	✓	✓	-	✓	✓	-	-	-	Heuristics and metaheuristics
Fathollahi-Fard et al. [58]	✓	✓	✓	✓	✓	-	-	✓	-	-	✓	✓	-	✓	-	Lagrangian relaxation based on ϵ -constraint
Liu et al. [63]	✓	-	✓	✓	✓	✓	-	-	✓	-	✓	-	✓	-	-	AMOALNS
This work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	Different version of NSGA-II and MILP

MSA: Modified Simulated Annealing. SA: Simulated Annealing. MOKA: Multiobjective Keshtel Algorithm. MOPSO: Multiobjective Particle Swarm Optimization. GA: Genetic Algorithm. ILP: Integer Linear Programming. EV: Electric Vehicle. VNS: Variable Neighborhood search. TS: Tabu Search. AMOALNS: combined Archived Multiobjective Simulated Annealing (AMOS) with Adaptive Large Neighborhood Search (ALNS).

3.1.1. Distance-based approach

When fuel consumption data is unavailable, CO₂ emissions can be calculated using distance, and the emission factor can be estimated based on the most appropriate value for each mode of transport. The emission factor depends on the average fuel consumption, which is influenced by the load factor and weight [9,14]. In this study, we utilize the distance-based approach. The calculation of CO₂ emissions is determined by the following formula (1):

$$CO_2.emission = distance.travel * emission.factor \quad (1)$$

The emission factor is calculated based on the estimated fuel conversion factor (2.61 kg.CO₂/liter of diesel) and the average fuel consumption, which is influenced by the load factor [9].

3.1.2. Fuel-based approach

The simplest and most reliable method to measure transport emissions is to monitor energy and fuel usage and convert them into CO₂ emissions using emission conversion factors. If absolute fuel consumption or distance traveled and average fuel consumption are available, the fuel-based method can be applied [14]. Absolute fuel consumption is first calculated (if unknown) based on the travel distance and average fuel consumption, which may depend on the type/model/engine of the vehicles [9]. Hence, absolute fuel consumption is calculated using the following formula (2):

$$absolute.fuel.consumption = distance.travel * average.fuel.consumption \quad (2)$$

CO₂ emissions are then calculated based on fuel consumption. First, fuel consumption is converted into energy using the fuel's heating value [9]. Next, the product is multiplied by the fuel's emission factor. Thus, the formulation of CO₂ emissions is determined by the following formula (3):

$$CO_2.emission = absolute.fuel.consumption * heating.value * emission.factor \quad (3)$$

It is important to note that since fuel consumption data is unavailable, we utilize the distance-based approach to estimate CO₂ emissions. Therefore, the emission factor is formulated as a function of the fuel conversion factor and the average fuel consumption, which depends on the vehicle's weight when empty and loaded. The load of HHC vehicles is determined by patient demand, which typically includes nursing medical tools and equipment for HHC services. The mathematical formulation of emissions is detailed in the following section.

4. Problem description and mathematical modeling

This section offers a comprehensive understanding of the problem and our proposed solution, structured into three subsections: problem description, the mathematical model for the first stage, and the mathematical model for the second stage. In the first subsection, we outline the context, objectives, and challenges faced by the HHC organization in scheduling caregivers over a planning horizon, introducing various objectives and constraints. The second and third subsections present the proposed mathematical models to address the GHHC routing and scheduling problem. The first stage mathematical model introduces a

multiobjective approach aiming to optimize routing and scheduling considering factors such as travel distance, CO₂ emissions, caregiver availability, patient care requirements, time windows, caregivers' workload capacity, precedence, synchronization constraints, and more. The second stage mathematical model subsection focuses on assigning appropriate caregivers to the routes generated in the first stage over a weekly planning horizon, considering caregiver skills, learning care, care continuity, and fairness in workload distribution.

4.1. Problem description

The objective of this study is to design the routes and schedule caregivers over a planning horizon (week) for the GHHC organization. We propose a new strategy that focuses on achieving multiple objectives. In addition to these objectives, we take into consideration various constraints that play a crucial role in the scheduling process. One important constraint is the affinity between patients and caregivers, ensuring that the assigned caregiver is compatible with the patient's preferences. We also consider the consistency between patients' needs and caregivers' skills, taking into account the patients' requests while considering the caregivers' expertise. Another constraint we consider is the availability of patients throughout the day, which requires visits to be made within specific time windows. This constraint ensures that the scheduling of caregivers aligns with the patients' availability.

In the presented model, the load depends on the demand for care. The demand for nursing medical tools and equipment includes test kits, first aid equipment, medication administration equipment, durable medical equipment, assistive technology, and meters/monitors. These devices are utilized by caregivers to provide care. The approach presented in this study has two stages: The first stage is structured to evaluate the packages (routes) that caregivers can take and consider all the scheduling and routing constraints. In the second stage, we allocate the packages to suitable caregivers and balance their weekly workloads.

4.2. First stage's mathematical model

In our study, we introduce the multiobjective model, which aims to optimize the assignment of packages over a single planning period. The primary objectives of this model are to minimize both travel distance and CO₂ emissions. To ensure continuity of care, caregivers are limited to a specific set of packages that they can be assigned to. We consider a complete directed network $G = (I, E)$, where I represents the patients' care and $E = \{(i, j) | i, j \in I, i \neq j\}$ denotes the set of arcs. Each patient may have a specific demand that needs to be delivered from the depot node. The routes begin at node 1 and conclude at the same node, which corresponds to the HHC organization. To model emissions, we adopt Molina et al. [83]'s approach because it has demonstrated its effectiveness in various studies, is suitable for MILP formulation, aligns well with our overall model, and adequately addresses the ecological sustainability aspect.

Parameters	
K	Set of packages (index k)
I	Set of cares (including the depot) (indexes i, j)
NAP_i	Set of the unavailable packages for care i (that care i cannot be assigned to)
S	Set of cares that require two caregivers ($S \subset I$)
R	Set of fuel type (index r)
s_i	Service time at care i
t_{ij}	Traveling time from node i to node j , $(i, j) \in E$
$[A_i, B_i]$	Respectively, the earliest and the latest service time for care i
MWL_k	Maximum daily workload for package k

ρ_i	Ratio of time decreased from care time s_i of care i
M	Very large number
prd_{ij}	Equal to 1 if care i has to be planned before care j and 0 otherwise
dis_{ij}	Distance between node i and j
q_i	Demand of care i
Q^k	Package k capacity
ξ_{kr}	Equal to 1 if the vehicle of package k uses fuel type r
$ef^{CO_2, r}$	Fuel conversion factor (amount of CO ₂ emitted per unit of fuel r consumed)
ep_k	Fuel consumption for an empty vehicle in package k
ap_k	Fuel consumption per unit of additional load for the vehicle in package k
J_i	Equal to 1 if care i requires one caregiver and 2 if the care requires two caregivers

Decision variables

x_{ijk}	Binary decision for assigning care j after care i in package k
y_{ik}	Binary decision for assigning care i to package k
AT_{ik}	Arrival time of package k to node i
l_{ijk}	Load carried by package k from nodes i to j
RT_{ik}	Remaining time at node i of package k (time left for package k at node i)

Objective functions:

$$\min \sum_{k \in K} \sum_{(i,j) \in E} x_{ijk} dis_{ij} \quad (4)$$

$$\min \sum_{k \in K} \sum_{(i,j) \in E} \sum_{r \in R} \xi_{kr} dis_{ij} ef^{CO_2, r} (x_{ijk} ep_k + ap_k l_{ijk}) \quad (5)$$

Constraints:

$$\sum_{k \in K} y_{jk} = J_j \quad \forall j \in I | j \neq 1 \quad (6)$$

$$\sum_{j \in I | j \neq 1} x_{1jk} \leq 1 \quad \forall k \in K \quad (7)$$

$$\sum_{j \in I | j \neq 1} x_{j1k} \leq 1 \quad \forall k \in K \quad (8)$$

$$y_{1k} = 1 \quad \forall k \in K \quad (9)$$

$$\sum_{k \in NAP_i} y_{ik} = 0 \quad \forall i \in I | i \neq 1 \quad (10)$$

$$y_{jk} = \sum_{i \in I | i \neq j} x_{ijk} \quad \forall k \in K \quad \forall j \in I \quad (11)$$

$$\sum_{i \in I} x_{ijk} = \sum_{i \in I} x_{jik} \quad \forall k \in K \quad \forall j \in I | j \neq 1 \quad (12)$$

$$AT_{jk} \geq A_j \quad \forall k \in K \quad \forall j \in I | j \neq 1 \quad (13)$$

$$AT_{jk} \leq B_j \quad \forall k \in K \quad \forall j \in I | j \neq 1 \quad (14)$$

$$\sum_{(i,j) \in E} ((s_i(1 - \rho_i)) + t_{ij}) x_{ijk} \leq MW L_k \quad \forall k \in K \quad (15)$$

$$AT_{jk} \geq AT_{ik} + ((s_i(1 - \rho_i)) + t_{ij}) x_{ijk} - (1 - x_{ijk}) M \quad \forall k \in K \quad \forall (i, j) \in E | j \neq 1 \quad (16)$$

$$AT_{jk} = AT_{jk'} \quad \forall (k, k') \in K \quad \forall j \in S \quad (17)$$

$$RT_{1k} = MW L_k \quad \forall k \in K \quad (18)$$

$$AT_{jk} \geq AT_{ik'} - (1 - pr_{dij})M \quad \forall (k, k') \in K \quad \forall (i, j) \in E \mid j \neq 1, i \neq 1 \quad (19)$$

$$RT_{jk} \leq RT_{ik} - ((s_i(1 - \rho_i)) + t_{ij})x_{ijk} + (1 - x_{ijk})M$$

$$\forall k \in K \quad \forall (i, j) \in E \mid j \neq 1 \quad (20)$$

$$q_j x_{ijk} \leq l_{ijk} \quad \forall k \in K \quad \forall (i, j) \in E \mid i \neq j \quad (21)$$

$$l_{ijk} \leq (Q^k - q_i)x_{ijk} \quad \forall k \in K \quad \forall (i, j) \in E \mid j \neq 1, i \neq j \quad (22)$$

$$x_{ijk} \in \{0, 1\}, y_{jk} \in \{0, 1\} \quad \forall k \in K \quad \forall j \in I \quad \forall i \in I \quad (23)$$

$$RT_{ik} \geq 0, AT_{ik} \geq 0, l_{ijk} \geq 0 \quad \forall k \in K \quad \forall j \in I \quad \forall i \in I \quad (24)$$

Objective (4) is formulated to minimize the total travel distance, while objective (5) aims to minimize CO₂ emissions; the first term ($\xi_{kr} \text{dis}_{ij} e f^{CO_2, r}$) calculates the distance traveled between nodes i and j by package k using fuel type r . ξ_{kr} ensures that only the appropriate fuel type's emission factor is used, then it converts fuel consumption into CO₂ emissions based on the specific fuel type r . The second term ($x_{ijk} ep_k + ap_k l_{ijk}$) calculates the total fuel consumption for the route between nodes i and j for package k . If $x_{ijk} = 1$, it implies that care j is assigned after care i in package k , so ep_k (fuel consumption for an empty vehicle) is added. Additionally, l_{ijk} represents the load carried by package k from node i to node j , so $ap_k l_{ijk}$ (fuel consumption per unit of additional load) is added. Constraint (6) ensures that each care has a specified number of caregivers assigned to it. To maintain the order of care, Constraint (7) limits the number of subsequent cares following a fictive care 1, while Constraint (8) restricts the number of preceding cares before fictive care 1. Constraint (9) guarantees that each caregiver is assigned to the HHC structure. Constraint (10) ensures that a package of cares adheres to specific restrictions, ensuring continuity in the planning. The routing variables x_{ijk} and assignment variables y_{ik} are linked in Constraint (11). Constraint (12) enforces the classical flow conservation constraint on the routing variables. Constraints (13) and (14) ensure that the start time of each care complies with predefined time windows. Constraint (15) limits the daily workload of caregivers to the duration of a workday, considering both service and travel times. Constraint (16) calculates the arrival time of the package at the care location. To synchronize cares, Constraint (17) ensures that multiple cares start simultaneously. The assignment of the same start time to all caregivers for care j is considered in Constraint (17), with variables y linked to the synchronization matrix (Constraint (6)), and variables y impacting variables x (Constraint (11)). Constraint (18) ensures that the workload of packages reaches its maximum at the depot. Constraint (19) maintains the precedence of cares. Constraints (20), (21), and (22) restrict the total load carried by a package based on travel and service times. Constraints (23) and (24) enforce the binary and non-negativity restrictions of the model, respectively.

4.3. Second stage's mathematical model

In this stage, our objective is to assign appropriate caregivers to the routes generated in the previous stage. To achieve this, we introduce a set called "category" which represents packages containing the same patients. A package belongs to one category. Parameters are inherited from the first stage model, except caregiver skill level. To ensure continuity of care throughout the planning horizon (week), we limit the categories to two packages per day based on the NSGA-II solution encoding. These packages are then assigned to skilled caregivers who possess the necessary abilities for the required care. The required skill level for a package ranges from "1" (basic skill) to "3" (advanced skill), depending on the maximum skill level required by the patients in the package. Caregivers, on the other hand, have three skill levels ranging from "1" (basic skill) to "3" (advanced skill). Caregivers can be

assigned to packages that match their skill level or require a lower skill level (e.g., a caregiver with skill level "2" can be assigned to packages requiring skill level "2" or "1"). To ensure equitable work distribution among caregivers, we have implemented a strategy to maximize the minimum caregiver utilization factor within the planning horizon [74]. Additionally, to enhance service quality, the workload of each caregiver must be managed and respected during each period [84]. Workload refers to the combined time spent by caregivers on daily service provision and travel. It is essential to ensure that the workload does not exceed the maximum allowable hours per day for caregivers.

To balance the workloads of the assigned caregivers, we propose a MILP model.

Parameters	
W	Set of caregivers (index w)
C	Set of categories (index c)
K_c	Set of packages in category c (index k)
D	Set of days in the planning horizon (index d)
$W L_{kd}$	Workload of package k on day d
sp_k	Skill required by the package k
sc_w	Skill of the caregiver w
F_{kd}	Binary assignment parameter indicating whether package k is assigned on day d and 0 otherwise
Decision variables	
z_{ckwd}	Binary assignment variable indicating whether the package k of category c is assigned to caregiver w on day d
$t_{ckw_1w_2}$	Binary assignment variable indicating whether the package k of category c is assigned to caregiver w_1 or caregiver w_2
m	Minimal operability factor of the caregiver that we aim to maximize in order to ensure a fairness workload

Objective function:

$$\max \quad m \quad (25)$$

Constraints:

$$z_{ckwd} = 0 \quad \forall c \in C \quad \forall k \in K_c \quad \forall w \in W \quad \forall d \in D \mid sp_k > sc_w \quad (26)$$

$$\sum_{w \in W} z_{ckwd} = F_{kd} \quad \forall c \in C \quad \forall k \in K_c \quad \forall d \in D \quad (27)$$

$$\sum_{c \in C} \sum_{k \in K_c} z_{ckwd} \leq 1 \quad \forall w \in W \quad \forall d \in D \quad (28)$$

$$\sum_{\substack{w \in W \\ w \neq w_1, w \neq w_2}} \sum_{d \in D} z_{ckwd} \leq (1 - t_{ckw_1w_2})M \quad \forall c \in C$$

$$\forall k \in K_c \quad \forall w_1, w_2 \in W \quad (29)$$

$$\sum_{w_1, w_2 \in W \mid w_1 \neq w_2} t_{ckw_1w_2} = 1 \quad \forall c \in C \quad \forall k \in K_c \quad (30)$$

$$t_{ckw_1w_2} = t_{ck'w_1w_2} \quad \forall c \in C \quad \forall k \in K_c \quad \forall k' \in K_c$$

$$\forall w_1 \in W \quad \forall w_2 \in W \mid w_1 \neq w_2 \quad (31)$$

$$\frac{\sum_{c \in C} \sum_{k \in K_c} \sum_{d \in D} z_{ckwd} W L_{kd}}{|D|} \geq m \quad \forall w \in W \quad (32)$$

$$t_{ckw_1w_2} \in \{0, 1\}, z_{ckwd} \in \{0, 1\}, m \geq 0 \quad (33)$$

Objective (25) ensures workload balancing. Constraint (26) guarantees that the packages are assigned to caregivers with matching

skills. Constraint (27) ensures the assignment of packages given by the first-stage model to the corresponding days. Constraint (28) guarantees that a caregiver is assigned to at most one package a day. Constraint (29) ensures linking between the decision variables z and t and limits the assignment of the packages to two caregivers of the category. Constraint (30) guarantees that each package in a category is assigned to one caregiver. Constraint (31) ensures that the packages of a category share the same caregivers. Constraint (32) ensures that each caregiver's workload is higher than the operability factor that we intend to maximize; it ensures that all caregivers have an equal workload and eliminates options where a caregiver has a lower workload than others. Constraint (33) enforces the binary variables of the model and the non-negativity restrictions.

5. Solution approach

This section provides a detailed insight into the solution approach, from algorithm selection to specific operators used in the optimization process. The first subsection introduces the NSGA-II algorithm and explains its application in solving the multiobjective problem of the first-stage GHHC. It covers the algorithm's components, advantages, and the process of generating a new population iteratively. The second subsection describes the encoding strategy proposed to represent the solution. It lists the constraints and criteria considered in the encoding process, followed by the proposed solution representation. Additionally, it explains how the encoding ensures feasibility and compliance with specified constraints. In the third subsection, the role of the selection operator in choosing parents for the reproduction process is discussed. It explains the binary tournament selection method used and its goal of guiding selection towards an optimal front. The fourth and fifth subsections describe in detail the crossover and mutation operator processes, respectively, including the selection of genes and the exchange of their positions. We also propose a heuristic to repair mutated offspring. In the last subsection, we present the Variable Neighborhood Descent (VND), which systematically explores different neighborhood structures to overcome local optima. Additionally, we introduce various versions of the NSGA-II algorithm enhanced by local search, offering systematic or periodic application options with different selection criteria for local search processes.

5.1. Implementation of NSGA-II for the first-stage GHHC

NSGA-II, introduced by Deb et al. [85], is an efficient Evolutionary Algorithm (EA) that utilizes Pareto dominance and natural selection [86]. It has demonstrated superior performance in solving multiobjective problems compared to previous EAs such as NSGA [87–89].

At each iteration, a new population of individuals, called offspring, is generated from the parent population using objective functions and algorithm operators. These offspring individuals are evaluated based on the objective function and compared to the parent population to select the most suitable individuals for the problem. This evolutionary process continues until a stop condition is met.

One of the notable advantages of NSGA-II is that it does not require a set of parameters to maintain diversity [9]. It employs a sorting method based on the concept of nondominance and adopts an elitist approach to preserve the best individuals. Additionally, it employs the crowding distance strategy, which estimates the density of solutions surrounding each individual. The crowding distance is calculated as the average distance between a solution and its neighboring solutions [81, 85].

In each iteration t , the parent population P_t of size N and the offspring population Q_t of size N are combined to form the population $R_t = P_t \cup Q_t$ with a size of $2N$. The individuals in R_t are sorted based on the nondomination concept, resulting in n Pareto fronts (F_1, F_2, \dots, F_n). The sorting procedure is employed to determine the individuals for the

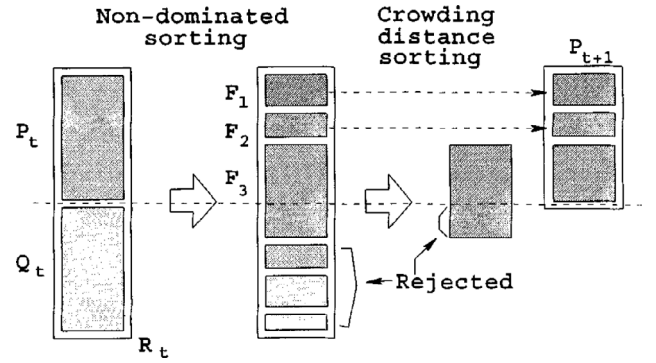


Fig. 1. NSGA-II procedure [85].

parent population P_{t+1} as long as its size is less than N . The crowding technique is applied to the remaining fronts (F_i not belonging to P_{t+1}) to select the best individuals. Finally, a new offspring population is constructed through selection, crossover, and mutation operations [85].

Fig. 1 shows the NSGA-II procedure [85].

The NSGA-II algorithm steps [85] are given in Algorithm 1.

Algorithm 1 Nondominated Sorting Genetic Algorithm II (NSGA-II)

```

1  $t = 0$ 
2  $P_t = \text{newpop}(N)$ 
3  $Q_t = \emptyset$ 
4 while no stop criterion do
5    $R_t = P_t \cup Q_t$  Combining parent and offspring population
6    $F = \text{fast-nondominated-sorting}(R_t)$  (all nondominated fronts of  $R_t$ )
7    $P_{t+1} = \emptyset, i = 1$ 
8   while  $|P_{t+1}| + |F_i| \leq N$  (until the parent population is filled) do
9     Crowding-distance-assignment ( $F_i$ )
10     $P_{t+1} = P_{t+1} \cup F_i$  include  $i$ th nondominated front in the parent  $P$ 
11     $i = i + 1$  check the next front for inclusion
12  end while
13  Sort ( $F_i, \prec_n$ ) sort in descending order using  $\prec_n$ 
14   $P_{t+1} = P_{t+1} \cup F_i[1 : (N - |P_{t+1}|)]$  choose the first  $(N - |P_{t+1}|)$  elements of ( $F_i$ )
15   $Q_{t+1} = \text{make-new-pop}(P_{t+1})$ . Use selection, crossover, and mutation to create
16  a new population  $Q_{t+1}$ 
17 end while

```

5.2. Solution encoding

The initial step in the process involves determining the allocation of packages to caregivers while considering a set of constraints and criteria. Some patients may require multiple treatments in a day, ranging from one to three, while others may not require any care on certain days.

To address these considerations, we propose a solution encoding that adheres to the following constraints and criteria:

- Patient availability
- Simultaneous synchronization
- Precedence synchronization
- Temporal dependency
- Continuity of care (limiting patient assignments to a specific number of caregivers)
- Maximum daily workload for caregivers
- Maximum vehicle package load
- Learning care (a static reduction of service time based on the day, independent of the route or caregiver)

The notation x_{12} represents the start time for care 1 of patient 1 with package 2. Our proposed encoding strategy aims to group packages with the same patients side by side. This technique ensures the feasibility of solutions even after crossover and reduces the complexity of correcting mutation offspring.

Table 2Proposed representation of the solution matrix (P).

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : Care_1$	x_{11}	0	0	0	0	0
$Patient_1 : Care_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : Care_3$	0	x_{32}	0	0	0	0
$Patient_3 : Care_4$	0	0	0	x_{44}	0	0
$Patient_3 : Care_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : Care_6$	0	0	0	x_{64}	0	0
$Patient_4 : Care_7$	0	0	0	0	0	x_{76}
$Patient_5 : Care_8$	0	0	0	0	0	x_{86}

The proposed solution encoding is presented in Table 2.

The program ensures the following conditions:

- Care 2 of patient 1 and care 5 of patient 3 are synchronized and require the presence of two caregivers. As a result, they are assigned twice, with $x_{21} = x_{22}$ and $x_{53} = x_{54}$ (the program ensures that the start of simultaneous synchronized care service is respected).
- The maximum daily workload for each package is respected and not exceeded.
- Time windows and the order of cares for patients are respected.
- The scheduling between treatments assigned to the same package is respected (temporal dependency).
- The allocation of packages to patients is limited to guarantee the continuity of care.
- The start of care for each patient is achievable (the schedule of care for each patient must be respected).
- The maximum load does not exceed the capacity of the package.

It is important to highlight that the encoding solution is consistently feasible and complies with all the specified constraints. An open-source code for the encoding solution is available in the following public repository.¹

5.3. Crowded tournament selection

The role of the selection operator is to choose the future parents for the reproduction process from the population of individuals.

In this study, we use a binary tournament selection. It involves randomly selecting two individuals from the population and then choosing the best-performing individual based on the crowded comparison operator. This selection mechanism aims to guide the choice towards an optimal front [85].

5.4. Crossover operator

The crossover operator ensures the diversity of solutions by merging the genetic information of two parents to generate two offspring children. In our approach, the crossover is performed by permuting the blocks of two different parents to create two offspring. We select the blocks of patients that contain all their cares to maintain feasibility after the crossover.

The combination of Parent Prt_1 (Table 3) and Parent Prt_2 (Table 4) gives offsprings E_1 and E_2 , as presented in Tables 5 and 6, respectively.

5.5. Mutation operator

The mutation operator plays a crucial role in overcoming local optima and maintaining solution diversity. In our approach, the mutation is performed as illustrated in Tables 7 and 8. It involves selecting a group of homogeneous packages. Then, two genes from different individuals within the selected group are randomly chosen, and their

Table 3Parent Prt_1 .

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : C_1$	x_{11}	0	0	0	0	0
$Patient_1 : C_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : C_3$	0	x_{32}	0	0	0	0
$Patient_3 : C_4$	0	0	0	x_{44}	0	0
$Patient_3 : C_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : C_6$	0	0	0	x_{64}	0	0
$Patient_4 : C_7$	0	0	0	0	0	x_{76}
$Patient_5 : C_8$	0	0	0	0	0	x_{86}

Table 4Parent Prt_2 .

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : C_1$	x_{11}	0	0	0	0	0
$Patient_1 : C_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : C_3$	x_{31}	0	0	0	0	0
$Patient_3 : C_4$	0	0	x_{43}	0	0	0
$Patient_3 : C_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : C_6$	0	0	x_{63}	0	0	0
$Patient_4 : C_7$	0	0	0	0	0	x_{76}
$Patient_5 : C_8$	0	0	0	0	0	x_{86}

Table 5Offspring E_1 .

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : C_1$	x_{11}	0	0	0	0	0
$Patient_1 : C_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : C_3$	x_{31}	0	0	0	0	0
$Patient_3 : C_4$	0	0	0	x_{44}	0	0
$Patient_3 : C_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : C_6$	0	0	0	x_{64}	0	0
$Patient_4 : C_7$	0	0	0	0	0	x_{76}
$Patient_5 : C_8$	0	0	0	0	0	x_{86}

Table 6Offspring E_2 .

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : C_1$	x_{11}	0	0	0	0	0
$Patient_1 : C_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : C_3$	0	x_{32}	0	0	0	0
$Patient_3 : C_4$	0	0	x_{43}	0	0	0
$Patient_3 : C_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : C_6$	0	0	x_{63}	0	0	0
$Patient_4 : C_7$	0	0	0	0	0	x_{76}
$Patient_5 : C_8$	0	0	0	0	0	x_{86}

Table 7Parent Prt_3 .

	P_1	P_2	P_3	P_4	P_5	P_6
$Patient_1 : C_1$	x_{11}	0	0	0	0	0
$Patient_1 : C_2$	x_{21}	x_{22}	0	0	0	0
$Patient_2 : C_3$	0	x_{32}	0	0	0	0
$Patient_3 : C_4$	0	0	0	x_{44}	0	0
$Patient_3 : C_5$	0	0	x_{53}	x_{54}	0	0
$Patient_3 : C_6$	0	0	0	x_{64}	0	0
$Patient_4 : C_7$	0	0	0	0	0	x_{76}
$Patient_5 : C_8$	0	0	0	0	0	x_{86}

positions are exchanged. The resulting offspring, denoted as E_3 , may potentially be infeasible. To address this, we propose heuristic 2 to test the feasibility of the mutated offspring.

The algorithm 2 is a heuristic for verifying the feasibility of mutation offspring in the scheduling problem, specifically functioning as a repair heuristic. It iterates over packages and cares, checking the feasibility of assignments based on constraints satisfaction. If an

¹ <https://github.com/SMAKBOUL/GHHC>.

Table 8Offspring E_3 .

	P_1	P_2	P_3	P_4	P_5	P_6
Patient ₁ : C_1	0	x_{11}	0	0	0	0
Patient ₁ : C_2	x_{22}	x_{21}	0	0	0	0
Patient ₂ : C_3	0	x_{32}	0	0	0	0
Patient ₃ : C_4	0	0	0	x_{44}	0	0
Patient ₃ : C_5	0	0	x_{53}	x_{54}	0	0
Patient ₃ : C_6	0	0	0	x_{64}	0	0
Patient ₄ : C_7	0	0	0	0	0	x_{76}
Patient ₅ : C_8	0	0	0	0	0	x_{86}

Algorithm 2: Heuristic for the verification mutation offspring feasibility.

```

1 input: Correction of mutation offspring
2 n: number of cares
3 p: number of packages
4 w, v, z: variables
5 for j from 1 to p
6   for i from 1 to n
7     if  $x_{ij} \neq 0$  (explore the first column package and find the nonzero value in row i)
8       for all feasible assignment of patient i by package j
9         for all values above row i in the current column
10          if  $x_{hj} \neq 0$  (find the first nonzero value in row h)
11            if load capacity is exceeded
12              z = 1
13              break
14            if  $x_{ij} \geq x_{hj}$ 
15              if  $x_{ij} < x_{hj} + s_h + t_{ih}$  the scheduling is not feasible between
16                care i and care h
17                  if  $\text{syn}(x_{ij}) = 1$ 
18                    v = 1
19                  else if  $\text{syn}(x_{ij}) = 0$ 
20                    w = 1
21                  break
22                end if
23              else if  $x_{ij} < x_{hj}$ 
24                if  $x_{hj} < x_{ij} + s_i + t_{jh}$  the scheduling is not feasible between
25                  care i and care h
26                    if  $\text{syn}(x_{ij}) = 1$ 
27                      v = 1
28                    else if  $\text{syn}(x_{ij}) = 0$ 
29                      w = 1
30                    break
31                  end if
32                end if
33              end if
34              if w = 1
35                 $x_{ij} = \text{newValue}(\text{feasible assignment for care i by package j})$ 
36              end if
37              if v = 1
38                 $x_{ij} = x_{ij+1} = \text{newValue}(\text{feasible assignment for care i by}$ 
39                  package j and care i by package j + 1)
40              else break
41            end if
42          end for
43          if z = 1 or all assignments of care with the current package are
44            not feasible with the scheduling of other cares with the same package
45            make  $x_{ij} = 0$ 
46            select the other package c
47             $x_{ic} = \text{rand}(B_i, A_i)$ 
48          end if
49          i = 1
50          j = 1 (test the new assignment)
51        end if
52      end for
53    end for

```

assignment is not feasible, it attempts to correct it by generating new feasible assignments. The algorithm also handles cases where all assignments with a particular package are infeasible, and proposes a feasible assignment. The goal is to ensure that the mutation offspring satisfies the necessary constraints for a valid schedule. It is worth mentioning

Table 9

NSGA-II versions.

Method	Frequency	Offspring solutions
NSGA-II	–	–
NSGA-II- α	Systematic	20% random
NSGA-II- β	Systematic	20% sorted
NSGA-II- γ	Periodic (number iterations = 20)	60%
NSGA-II- δ	Periodic (number iterations = 20)	100%

that $\text{syn}(x_{ij})$ is equal to 1 if care i requires simultaneous synchronization and 0 otherwise.

5.6. Variable neighborhood descent

Variable Neighborhood Descent (VND) is a local search heuristic that systematically explores different neighborhood structures. Its effectiveness lies in the fact that different neighborhoods often contain different local minima, allowing it to overcome the problem of getting trapped in local optima. This is achieved through deterministic modifications of the neighborhood [90,91]. In the case of the VRP, local search procedures are applied to the problem. The neighborhood of a current solution is defined by the set of solutions obtained by applying local transformations, referred to as “moves”, to the current solution. In this study, four neighborhoods are considered, involving rearrangements of cares within packages and exchanges of cares between packages and routes. The VND is implemented according to Algorithm 3, where $\alpha_{\max} = 4$ represents the exploration of four neighborhoods of the solution S . A solution S' in the neighborhood α (denoted as $N_\alpha(S)$) is considered an improvement if it is the best solution according to the concept of dominance. Specifically, if $F_1(S) < F_1(S')$ and $F_2(S) \leq F_2(S')$, or if $F_1(S) \leq F_1(S')$ and $F_2(S) < F_2(S')$.

Algorithm 3 Variable Neighborhood Descent

```

1  $\alpha$ : Neighborhood
2 S: Initial solution
3 L: List of neighborhood indexes
4 i ← 1
5 while (i ≤  $\alpha_{\max}$ )
6    $S^*$ : First solution in  $N_\alpha(S)$ 
7    $\alpha = L[i]$ 
8   if  $S^*$  dominates S
9      $S \leftarrow S^*$ 
10    i ← 1
11  else
12    i ← i + 1
13  end if
14 end while

```

Different parameter settings for the NSGA-II algorithm, enhanced by the inclusion of local search, are tested and evaluated. The local search can be applied either periodically or systematically. In the case of systematic local search, it is performed at each generation, while periodic local search is conducted after a certain number of iterations. In the systematic versions, approximately 20% of the offspring population individuals are selected for the local search process. The selection can be random or based on non-dominance criteria. On the other hand, in the periodic versions, either 60% or 100% of the offspring population individuals undergo the local search. Table 9 provides an overview of the different versions of NSGA-II with local search, highlighting the specific parameter settings used. Algorithm 4 outlines the steps of the NSGA-II algorithm incorporating the local search procedure. It is worth mentioning that the four versions of NSGA-II enhanced by local search uses the same operators (crowding distance, etc.) as the standard NSGA-II.

Algorithm 4 NSGA-II enhanced by local search

```

1  Initializing solution
2  Using crossover, mutation
3  Sorting the individuals using NSGA-II operators
4  Using local search heuristics
5  Evaluate and ranking the individuals using dominance
6  If the stopping criterion is met
7      return the Pareto front
8  else
9      Go to Step 2
10 end if

```

6. Computational results

The NSGA-II algorithm was implemented using the C programming language and executed on an HP Intel Core i5 personal computer with a clock speed of 2.2 GHz and 6 GB of RAM. The CodeBlocks environment was utilized for the execution. To solve the mathematical models, CPLEX 12.6 was employed, and the computations were carried out on a Dell Intel Core i7 machine with a clock speed of 3.40 GHz and 16 GB of RAM.

6.1. Instance generation

In the experimental analysis, we utilized the existing benchmark instances [15] and generated additional random data specific to the HHC. Each patient is characterized by several factors, including the number of cares required per day, the order of the cares, and whether a care requires the presence of two caregivers. The additional data is predominantly generated using a uniform distribution. The series of care required by patients is modeled to follow a uniform distribution of $\mathcal{U}[0, 3]$, while the data for synchronization and precedence is assumed to adhere to a uniform distribution of $\mathcal{U}[0, 1]$. The precedence sequences are selected randomly from all possible scenarios. To represent a particular instance, we used the notation I.PXCYKZ, where I denotes the instance, X represents the number of patients, Y represents the number of cares, and Z represents the number of caregivers. The experiments are conducted over a one-week horizon, excluding school holidays and public holidays. Benchmarks are available in the following public repository.²

An example of the cares required by patients is presented in Table 10, where the notation (SYN) indicates that the care requires the presence of two caregivers simultaneously.

6.2. Experimental results and analysis**6.2.1. First stage results**

The quality of the results is influenced by the selection of parameters. To determine the suitable values for these parameters, we executed the algorithm multiple times. A preliminary research process was conducted to identify the best values for the population size and maximum generation. Table 11 presents the optimal values obtained through this exploration. Additionally, we experimented with different combinations of crossover probability and mutation probability coefficients in order to provide a range of variations.

The data analysis indicates that, in most instances, a lower mutation coefficient leads to improved solution values, particularly when combined with a higher crossover value. To explore this further, we defined four scenarios for the crossover probability values (0.2, 0.4, 0.6, and 0.8) and four scenarios for the mutation probability values

Table 10

Data about care for instance 1.P20C40K10.

Patient	Care α	Care β	Care γ
1	(+) before β (SYN)	(+)	(-)
2	(+) before β	(+) before γ	(+)
3	(+) before β (SYN)	(+)	(-)
4	(+) before β	(+)	(-)
5	(+) before β	(+)	(-)
6	(+)	(+) before α	(-)
7	(+) before β	(+)	(-)
8	(+) before β	(+)	(-)
9	(+)	(+) before α	(-)
10	(+) before β	(+)	(-)
11	(+) before β	(+)	(-)
12	(+) before β	(+)	(-)
13	(+) before β	(+)	(-)
14	(+)(SYN)	(+) before α	(-)
15	(+) before β	(+)	(-)
16	(+) before β	(+)	(-)
17	(+) before β	(+)	(-)
18	(+) before β	(+) (SYN)	(-)
19	(+)(SYN)	(+) before α	(-)
20	(-)	(-)	(+)(SYN)

Table 11

Values of parameters.

Parameter	Value
Population size	100
Maximum generation	120

Table 12

Values of parameters guaranteeing best solutions.

Instance	Crossover probability value	Mutation probability value
1.P20C40K10	0.8	0.2
2.P20C41K10	0.6	0.2
3.P40C80K12	0.6	0.2
4.P40C84K12	0.8	0.2
5.P60C115K14	0.8	0.2
6.P60C120K14	0.8	0.4
7.P80C160K16	0.8	0.2
8.P80C166K16	0.8	0.2
9.P100C196K18	0.8	0.2
10.P100C200K18	0.8	0.2
11.P150C300K22	0.6	0.2
12.P150C315K22	0.8	0.2
13.P200C400K24	0.8	0.4
14.P200C420K24	0.8	0.4

(0.2, 0.3, 0.4, and 0.5). Based on the findings presented in Table 12, we determined that a crossover coefficient of 0.8 and a mutation coefficient of 0.2 provide better results.

We utilize the ϵ -constraint algorithm to compute the optimal Pareto front for small-size instances. The ϵ -constraint assists in identifying a set of optimal solutions by prioritizing one objective while treating others as constraints within a specified tolerance (ϵ) [92]. It balances trade-offs to generate a Pareto front of solutions. The travel distance is considered the main objective function. We utilize the Julia package vOptSolver [93]. Table 13 compares the results between NSGA-II and the ϵ -constraint method. Computational results are obtained within a time limit of 3600 s.

Table 14 displays the results obtained from both the standard NSGA-II and the local search-based methods for 14 instances, each involving a maximum of 200 patients (400 care packages). For each instance, we present two possible solutions from the Pareto Front.

The results indicate that the NSGA-II algorithm incorporating local search consistently outperforms the standard NSGA-II in nearly all instances. Although the computation time increases for the local search-based methods compared to the standard NSGA-II approach, the maximum computation time remains at approximately 48 s, even for an instance with 200 patients. This demonstrates the efficiency of the

² <https://github.com/SMAKBOUL/GHHC>.

Table 13Comparison between standard NSGA-II and ϵ -constraint.

	NSGA-II						ϵ -constraint					
	Distance			Emissions			Distance			Emissions		
	Min	Max	Average	Min	Max	Average	Min	Max	Average	Min	Max	Average
1.P20C40K10	630	720	675	149	176	162	610	702	656	139	163	151
2.P20C41K10	681	695	688	160	192	176	652	682	667	137	165	151
3.P40C80K12	2241	2389	2315	950	1023	987	1120	1229	1175	942	1003	973
4.P40C84K12	2131	2389	2253	872	1035	954	2136	2484	2310	744	866	805

Table 14

Computational results obtained using standard NSGA-II and local search methods.

Instance	NSGA-II			NSGA-II- α			NSGA-II- β			NSGA-II- γ			NSGA-II- δ		
	Distance (km)	Emissions (kg.CO ₂)	CPU (s)	Distance (km)	Emissions (kg.CO ₂)	CPU (s)	Distance (km)	Emissions (kg.CO ₂)	CPU (s)	Distance (km)	Emissions (kg.CO ₂)	CPU (s)	Distance (km)	Emissions (kg.CO ₂)	CPU (s)
1.P20C40K10	629	176	1.224	622	174	20.65	613	175	17.36	707	203	11.63	725	156	11.75
	703	168		645	172		620	168		701	214		711	216	
2.P20C41K10	685	188	1.890	684	186	25.96	677	180	17.96	911	189	12.87	924	138	11.98
	691	166		681	189		669	184		899	203		913	143	
3.P40C80K12	2260	1022	2.292	2263	1013	25.45	1220	1020	18.26	2250	1301	13.85	2276	1342	11.74
	2371	993		2273	1009		1229	1009		2236	1313		2280	1333	
4.P40C84K12	2371	898	2.287	2366	861	26.23	2309	859	18.74	2313	889	14.68	2398	866	12.74
	2136	1003		2326	877		2289	861		2303	894		2205	894	
5.P60C115K14	1831	802	2.523	1799	809	28.32	1796	817	20.69	1855	811	15.75	1819	816	13.58
	1851	766		1812	801		1802	825		1819	821		1839	806	
6.P60C120K14	1911	798	2.403	1889	775	28.69	1893	796	21.77	1901	786	16.75	1996	792	14.85
	1841	843		1881	802		1906	752		1894	798		1977	786	
7.P80C160K16	3823	1686	2.932	3980	1650	28.96	3901	1540	23.71	3901	1690	17.52	3899	1632	15.75
	4037	1628		3980	1671		3698	1555		3862	1698		3898	1634	
8.P80C166K16	3816	1690	3.102	3796	1679	30.32	3624	1674	29.54	3798	1654	18.96	3799	1680	15.25
	4236	1679		3799	1670		3812	1664		3766	1677		3787	1689	
9.P100C196K18	4694	1935	3.119	4691	1949	30.91	4712	1978	35.25	4713	1933	19.25	4694	1924	16.25
	4688	1939		4681	1920		4736	1969		4702	1945		4685	1935	
10.P100C200K18	4678	1969	3.110	4651	1945	31.85	4763	1986	34.96	4693	1973	20.85	4597	1971	18.74
	4598	1986		4522	1973		4803	1981		4598	1985		4604	1986	
11.P150C300K22	5925	2422	11.749	5873	2401	32.11	5902	2389	401.96	5910	2389	24.98	5934	2401	19.47
	5880	2429		5871	2410		5887	2398		5866	2408		5896	2456	
12.P150C315K22	6080	2389	10.473	6032	2344	35.45	5896	2397	35.97	6033	2375	26.78	6019	2349	21.74
	5981	2439		5989	2393		5888	2405		6003	2409		6037	2334	
13.P200C400K24	6233	2658	15.024	6210	2660	39.11	6298	2569	44.47	6214	2699	28.96	6218	2694	21.78
	6486	2598		6290	2659		6223	2603		6245	2574		6235	2678	
14.P200C420K24	7196	2397	17.024	7186	2365	48.91	6968	2307	40.75	7139	2381	30.74	7194	2384	22.85
	6976	2401		6989	2567		6901	2325		6934	2396		7184	2402	

proposed approach. It is noteworthy from Table 14 that minimizing the travel distance does not necessarily guarantee a reduction in CO₂ emissions.

Given the correlation between travel distance and CO₂ emissions [9], the cardinality of the Pareto front solutions remains small, as both objectives are formulated as functions of distance. The computational time increases with the size of the instances due to the algorithmic complexity and the crowding distance, which follows an $O(MN \log N)$ complexity [85], where M represents the number of objectives and N represents the population size.

Fig. 2 illustrates the Pareto front obtained by the proposed methods for the instance (1.P20C40K10). The figure highlights the diversity of solutions achieved by all the methods. Moreover, the distribution of solutions in the NSGA-II- α method outperforms the other methods. Further statistical analysis is elaborated in the subsequent section.

Statistical analysis and metric measurements. To assess the quality of solutions obtained using the NSGA-II approach, several performance metrics are used, including the Inverted Generational Distance (IGD) metric, Diversification (D), Distribution (DIS), and the Hypervolume (HV) [9,94].

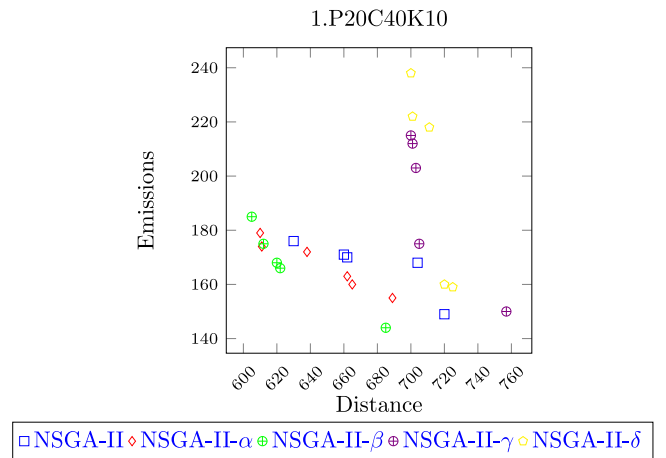
**Fig. 2.** Pareto front obtained by the methods for the instance 1.P20C40K10.

Table 15
Results of metrics.

	IGD				DIS				D(×10)				HV							
Instance	Version																			
	NSGA-II	NSGA-II- α	NSGA-II- β	NSGA-II- γ	NSGA-II- δ	NSGA-II	NSGA-II- α	NSGA-II- β	NSGA-II- γ	NSGA-II- δ	NSGA-II	NSGA-II- α	NSGA-II- β	NSGA-II- γ	NSGA-II- δ	NSGA-II	NSGA-II- α	NSGA-II- β	NSGA-II- γ	NSGA-II- δ
1.P20C40K10	2.014	2.120	1.97	2.138	2.703	3.256	2.272	4.894	4.214	3.016	8.246	9.231	9.103	8.623	8.341	0.39	0.28	0.38	0.57	0.35
2.P20C41K10	2.023	2.001	2.111	2.121	2.626	2.746	2.263	3.954	3.953	4.104	8.145	8.131	9.178	8.741	8.374	0.40	0.21	0.58	0.45	0.2
3.P40C80K12	2.121	2.105	2.018	2.145	2.727	2.946	2.942	3.264	3.041	3.952	8.315	9.574	8.745	8.985	8.237	0.52	0.29	0.61	0.44	0.63
4.P40C84K12	2.120	2.171	1.910	2.087	2.689	2.868	2.869	3.127	3.126	3.845	8.985	9.898	8.861	8.698	8.225	0.78	0.22	0.95	0.57	0.33
5.P60C115K14	2.140	2.208	2.219	2.197	2.707	2.264	5.078	7.104	6.617	6.856	8.185	9.128	8.187	8.778	8.158	0.83	0.12	0.47	0.71	0.25
6.P60C120K14	2.451	2.231	2.293	2.189	2.675	2.352	2.014	3.216	2.326	2.749	8.465	9.236	8.367	8.985	8.492	0.87	0.18	0.95	0.72	0.39
7.P80C160K16	2.078	2.046	1.947	2.269	2.984	2.468	2.318	2.056	2.951	2.947	8.410	9.174	8.945	8.963	8.146	0.78	0.92	0.45	0.51	0.39
8.P80C166K16	2.001	2.078	1.984	2.123	2.969	2.127	2.295	2.197	2.827	2.927	8.607	9.074	8.819	8.719	8.314	0.52	0.83	0.61	0.44	0.43
9.P100C196K18	2.691	2.175	2.345	2.115	2.686	9.068	24.294	12.176	12.764	22.815	8.395	9.086	8.863	8.817	8.295	0.21	0.75	0.39	0.65	0.10
10.P150C200K18	2.369	2.102	2.236	2.145	2.621	2.258	3.289	3.108	3.564	3.141	8.478	8.996	8.145	8.803	8.234	0.21	0.74	0.38	0.42	0.15
11.P150C300K22	2.190	2.131	2.261	2.162	2.688	2.085	1.984	1.627	2.099	2.945	8.871	8.961	8.981	8.678	8.584	0.71	0.85	0.62	0.18	0.57
12.P150C315K22	2.012	1.992	2.001	2.112	2.468	2.489	3.964	3.127	3.624	3.654	8.741	9.251	8.171	8.759	8.214	0.29	0.76	0.42	0.51	0.18
13.P200C400K24	2.285	2.212	2.216	2.048	2.638	6.548	6.489	6.985	7.145	7.012	8.301	9.179	8.861	8.917	8.345	0.25	0.76	0.33	0.32	0.18
14.P200C420K24	2.014	1.942	1.851	2.310	2.672	2.054	1.936	2.310	2.127	2.452	8.011	8.947	8.741	8.936	8.234	0.25	0.88	0.73	0.47	0.59

The IGD metric measures the proximity of a set of solutions to the Pareto front [9,94]. It is calculated using the formula (34):

$$IGD = \frac{1}{|F|} \sum_{f \in F} d(f, X) \quad (34)$$

where X is the Pareto front found, $d(f, X)$ is the minimum distance between solution f and set X , and F is the approximation set. An approximation set is considered as a set in which no element in F dominates or is equal to any other objective vector in the set [95]. The algorithm is considered efficient when the IGD value is minimized [96]. The DIS metric introduced by Goh and Tan [97] and based on Schott [98]. It is formulated as follows:

$$DIS = \frac{1}{|Q|} \sqrt{\frac{1}{|Q|} \sum_{i=1}^{|Q|} (d_i - \bar{d})^2} \quad (35)$$

$$\bar{d} = \frac{1}{|Q|} \sum_{j=1}^{|Q|} d_j \quad (36)$$

The diversification metric, denoted as (D), measures the diversity of solutions obtained from the Pareto front [99,100]. It is calculated using the formula (37):

$$D = \sqrt{\sum_{i=1}^N (\max f_i - \min f_i)^2} \quad (37)$$

In this equation, N represents the number of objectives, $\max f_i$ denotes the maximum value of objective i , and $\min f_i$ represents the minimum value of objective i . A higher value of D indicates a greater diversity among the members in the Pareto front [99,100].

Additionally, the DIS metric can also be used to assess the distribution of solutions in the Pareto front. It measures the uniformity of the solutions and can be calculated as the average Euclidean distance in objective space between a solution and its nearest neighbor in the nondominated set [101]. A smaller value of the DIS metric indicates a more evenly distributed set of solutions in the Pareto front [97].

HV is a performance metric that quantifies the quality of the non-dominated solutions. We use it to evaluate the trade-offs between Pareto fronts obtained from the standard NSGA-II and local search based algorithms. A higher HV value indicates a larger region of dominated space covered by the non-dominated solutions, signifying a better overall performance of the algorithm in terms of finding a diverse set of solutions. We have incorporated the HV metric and normalized the objective functions for each instance and method to obtain an accurate value between 0 and 1 for comparison. We used Julia JuMP [102] to compute it.

Table 15 presents the results of the performance metrics obtained from running the algorithm five times on each instance and calculating the average metric value. The IGD values indicate that the solutions are relatively close to the Pareto front, as the values are not large. This suggests that the algorithm is effective in finding solutions that are in proximity to the optimal front [96].

The D metric values are large, indicating a high level of diversity among the solutions in the Pareto front. This demonstrates the algorithm's ability to generate a wide range of diverse solutions [99, 100].

In terms of the DIS metric, the values for all instances are small and close to zero. This implies that the solutions are well-distributed across the Pareto front, indicating a good spread of solutions [97,101]. However, in instances 13, 9, and 5, the solutions appear to be less evenly distributed in the front.

Based on the results obtained from the HV indicator, it can be observed that NSGA-II- α provides better quality of non-dominated solutions for large instances compared to other versions. For medium-sized instances, NSGA-II- β is more dominant.

The results show that the local search methods outperform the standard NSGA-II algorithm across all four performance metrics. Although the local search methods require more computational time, the execution time remains below 49 s even for the largest instances of the problem. This demonstrates the efficiency of the proposed approach and its feasibility for implementation.

6.2.2. Second stage results

The second stage aims to assign the caregivers to the designed routes while balancing their workloads and ensuring the continuity of care.

Table 16 provides the results obtained from solving the second-stage problem. In Table 17, the obtained planning for instance 1.P20C40K10 is presented, taking into account the continuity of care. The learning care factor is set to 0.2, starting from day 3. As expected, the computation time, number of variables, and number of constraints increase with the size of the instances.

Based on the problem constraints, a group of caregivers is assigned to the care packages, ensuring a balanced workload for the caregivers to the best extent possible. In Table 16, the presence of a “*” in the gap column indicates that the solver has reached the imposed gap of 1.e-4. Conversely, a “~” in the computation time column suggests that the solver took more than two hours without reaching the imposed gap. The last column in Table 16 displays the average number of caregivers per patient for each instance. The results indicate that the continuity of care is maintained, with an average of less than two caregivers per patient.

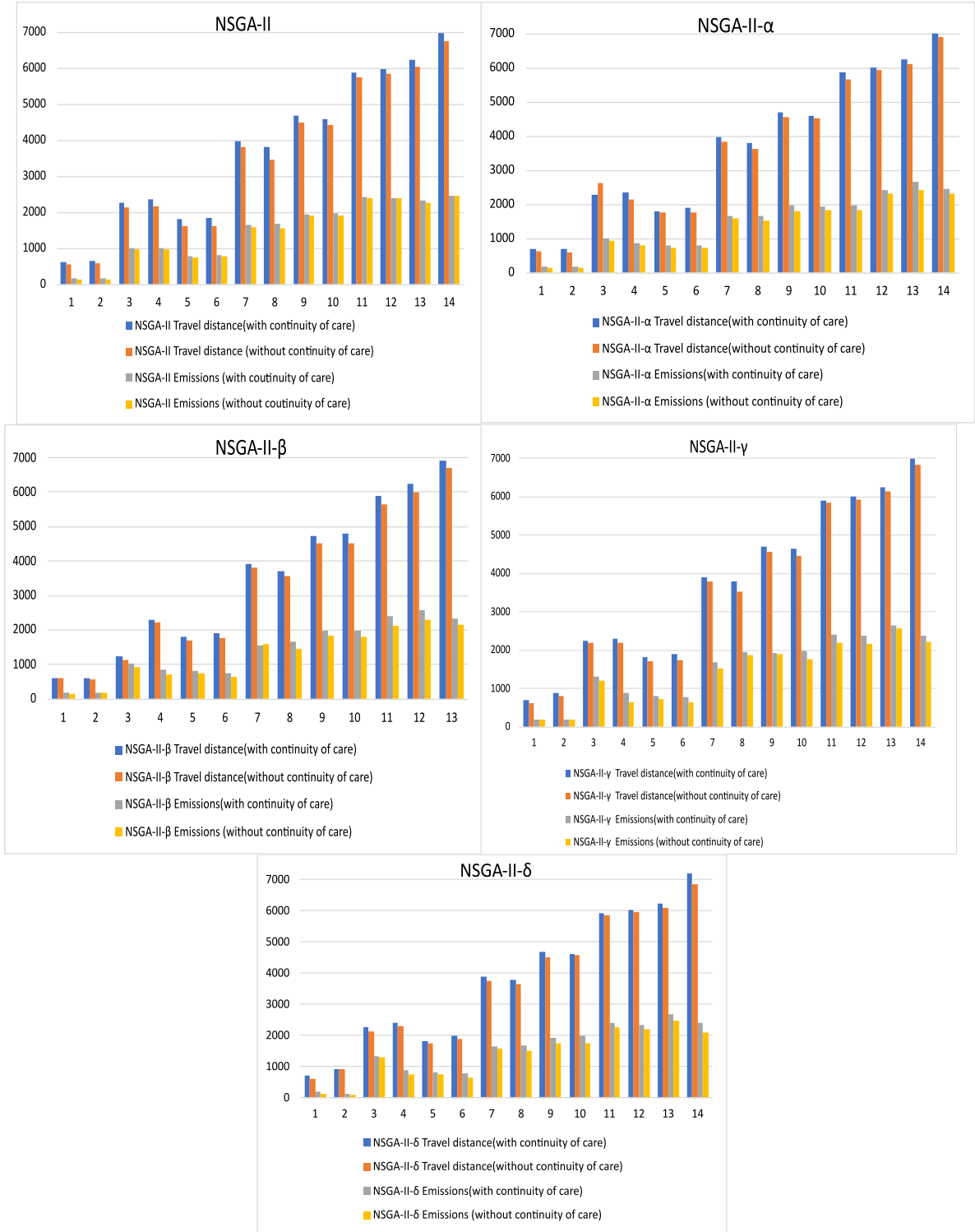


Fig. 3. Results obtained by the methods with and without continuity of care.

Impact of continuity of care. In this paragraph, we explore the alternative of not considering the continuity of care in the proposed approach. By not incorporating the continuity of care, the coding of the initial solution for the NSGA-II algorithm becomes simpler compared to the approach presented in Section 5. Patients can be assigned to any package without any restrictions. In the second stage model, only a subset of constraints needs to be considered, specifically (26), (27), (28), (32), and (33). Additionally, the parameters “category” and the variable $t_{ckw_1w_2}$ can be removed from the model.

Fig. 3 illustrates the trend of the objective function with and without continuity of care. The x-axis represents the instances (1 refers to 1.P20C40K10, and 2 refers to 2.P20C41K10 up to 14, which corresponds to 14.P20C420K24, and so on). The y-axis represents the quantity of emitted CO₂ or the distance traveled. We observe that not considering continuity of care results in reduced CO₂ emissions and total travel distance for both the standard NSGA-II and the local search-based methods in almost all instances. Across all methods and instances, the total distance without continuity of care is either equal

Table 16
Numerical results' second-stage problem.

Instance	Objective function	# of variables	# of constraints	CPU (s)	GAP (%)	Mean # of caregivers per patient
1.P20C40K10	0.8	1512	2930	360.36	*	1.75
2.P20C41K10	0.8	1512	2930	376.49	*	1.75
3.P40C80K12	0.8	2462	3480	230.73	*	1.9
4.P40C84K12	0.8	2462	3480	593.78	*	1.8
5.P60C196K14	0.6	3740	8022	379.25	*	1.8
6.P60C120K14	0.6	3740	8022	1745.23	*	1.9
7.P80C160K16	0.8	5394	11 984	2065.98	*	1.87
8.P80C166K16	0.8	5394	11 984	2611.85	*	1.8
9.P100C196K18	0.5	7472	17 082	~	1.25	1.9
10.P100C200K18	0.5	7472	17 082	~	4.23	1.9
11.P150C300K22	0.4	13 070	31 240	~	1.35	1.86
12.P150C315K22	0.4	13 070	31 240	~	4.26	1.9
13.P200C400K24	0.3	15 314	37 236	~	1.35	1.86
14.P200C420K24	0.3	15 314	37 236	~	3.35	1.9

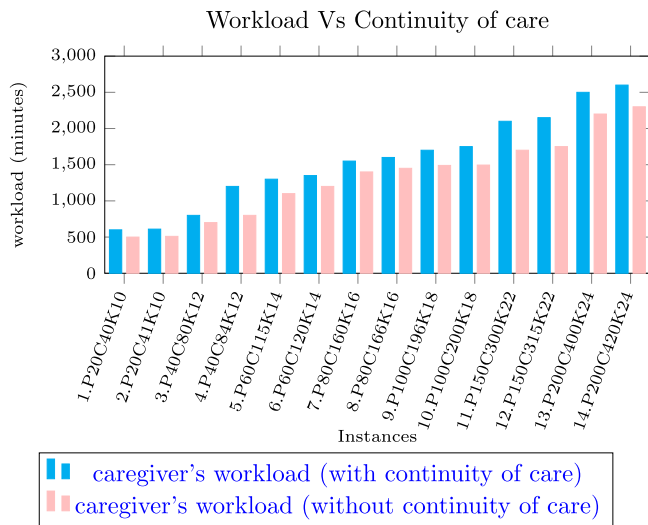


Fig. 4. The weekly workload of the caregivers with and without the continuity of care (minutes).

Table 17
Planning of instance 1.P20C40K10.

Day	Package									
	P1	P3	P2	P5	P10	P7	P6	P9	P8	P4
MONDAY	Cg(a)	Cg(b)	Cg(g)	Cg(e)	Cg(j)	Cg(h)	Cg(d)	Cg(f)	Cg(c)	Cg(i)
TUESDAY	-	Cg(i)	Cg(a)	Cg(d)	Cg(f)	Cg(h)	Cg(e)	Cg(j)	Cg(c)	Cg(b)
WEDNESDAY	-	Cg(i)	Cg(a)	Cg(d)	-	Cg(h)	Cg(e)	Cg(j)	Cg(h)	Cg(b)
THURSDAY	Cg(a)	Cg(b)	Cg(g)	Cg(e)	-	Cg(c)	Cg(d)	Cg(f)	-	Cg(i)
FRIDAY	Cg(g)	Cg(i)	Cg(a)	Cg(d)	Cg(f)	Cg(c)	Cg(e)	Cg(j)	Cg(h)	Cg(b)

Cg: Caregiver.

to or smaller than the total distance when continuity is considered, with the exception of instance 3 in the NSGA-II- α method. On the other hand, considering continuity of care impacts CO₂ emissions. However, there are a few instances where CO₂ emissions remain the same for both cases. For instance, NSGA-II instances 1, 11, and 14, NSGA-II- α instance 1, NSGA-II- β instance 2, and NSGA-II- γ instances 1 and 2 show no significant difference in CO₂ emissions. This observation suggests that for small instances, continuity of care does not significantly influence the amount of emitted CO₂.

Table 18 presents results obtained without the continuity of care constraints. The reduction in the number of variables, constraints, and computational time indicates that not considering continuity of care strengthens the balance of caregivers' workloads. Optimal solutions are achieved for all instances, and computation time is significantly

reduced. However, one downside is that the number of caregivers assigned to patients has increased. The average number of caregivers per patient exceeds 2, which may lead to patient dissatisfaction.

Fig. 4 showcases the weekly workload of caregivers with and without continuity of care. The intervention of the learning factor ensures that continuity of care reduces the weekly workload of caregivers. Conversely, ignoring continuity of care may result in minimal distances and emissions. However, it can impact the satisfaction of both caregivers and patients, as patients generally prefer to be visited by the same caregivers. This highlights the importance of considering continuity of care to enhance satisfaction levels.

7. Sensitivity analysis

The sensitivity analysis is conducted using the most compromising solution for the NSGA-II on each objective for time windows and instance sizes. A small time window refers to $[A_i, B_i]$, medium to $[A_i - 30, B_i + 30]$, and large to $[A_i - 60, B_i + 60]$. For time windows, we take the average of NSGA-II's most compromising solutions. As the time window size increases from small to large, both the distance and emissions decrease. This suggests that larger time windows result in more efficient routes with lower distance and emissions. Similarly, as the instance size increases, both the distance and emissions also increase. As observed in the results analysis, the local search methods performed better than the standard NSGA-II on some instances (such as 40 patients). However, the trend suggests that larger instances result in longer routes with higher distance and emissions. These sensitivity analyses provide insights into how changes in time window size and instance size affect the performance metrics of distance and emissions in each scenario (see Fig. 5).

8. Managerial insights

This study introduces an innovative, environmentally friendly approach to tackle the HHC problem, with a focus on optimizing scheduling and routing processes while minimizing environmental impact. It provides invaluable managerial insights for HHC managers grappling with a set of complex constraints and criteria. By considering a multitude of challenging constraints and acknowledging the multiobjective nature of the problem, this research makes a significant contribution to the field of HHC. It underscores the necessity of adapting efficient operations research algorithms to handle such complexities effectively.

The proposed solution entails a two-stage model. In the first stage, routes for caregivers are meticulously designed to cater to multiple patients, while the second stage prioritizes balancing caregivers' workloads. By formulating the problem as a bi-objective programming model and integrating constraints pertinent to HHC, the study ensures efficient resource allocation and patient care. Algorithm performance is evaluated using advanced metrics, highlighting the effectiveness of local search methods in enhancing solution quality.

Table 18
Numerical results' second-stage problem (without continuity of care).

Instance	Objective function	# of variables	# of constraints	CPU (s)	GAP (%)	Mean # of caregivers per patient
1.P20C40K10	1	512	120	0.24	*	2.25
2.P20C41K10	1	512	120	0.16	*	2.25
3.P40C80K12	0.8	734	156	1.80	*	2.65
4.P40C84K12	0.8	734	156	2.42	*	2.5
5.P60C115K14	0.8	996	168	39.79	*	2.5
6.P60C120K14	0.8	996	168	36.30	*	2.5
7.P80C160K16	0.9	1298	192	600.78	*	2.125
8.P80C166K16	0.9	1298	192	703.85	*	2.25
9.P100C196K18	0.8	1640	216	696.74	*	2.5
10.P100C200K18	0.8	1640	216	623.45	*	2.5
11.P150C300K22	0.8	1893	342	1286.25	*	2.44
12.P150C315K22	0.8	1893	342	1402.63	*	2.5
13.P200C400K24	0.9	2146	469	1896.98	*	2.425
14.P200C420K24	0.9	2146	469	1936.47	*	2.5

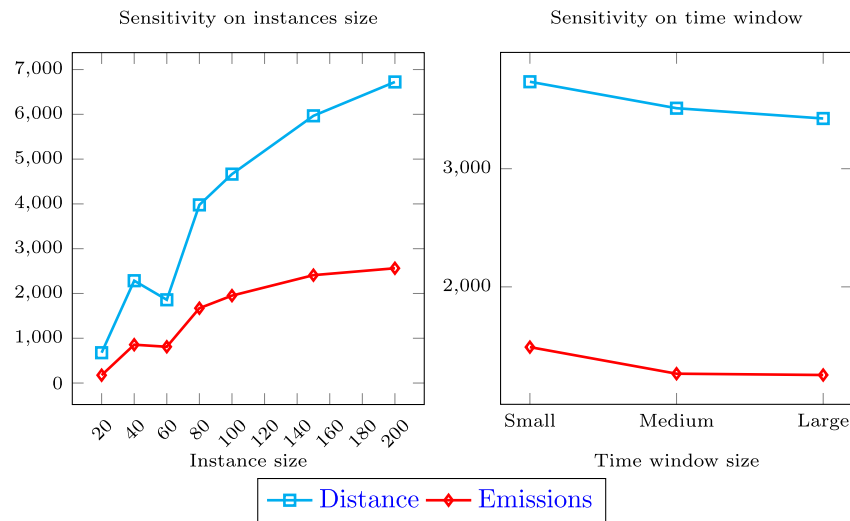


Fig. 5. Sensitivity analysis on instances and time window.

Through these insights, we offer actionable operational strategies to HHC organizations, aimed at enhancing patient care, reducing costs, and mitigating environmental impact, all while addressing the challenges of scheduling and routing in HHC settings. Our study has been rigorously tested on a large set of benchmarks and is readily applicable to HHC organizations, considering various practical factors that influence implementation feasibility.

Insights gleaned from the absence of continuity of care underscore significant trade-offs. While removing these constraints simplifies the solution encoding and improves workload balance, it risks increasing the number of caregivers per patient and potentially impacting overall satisfaction. However, it is crucial to emphasize the paramount importance of continuity of care for HHC organizations. Maintaining continuity ensures higher levels of patient satisfaction and quality of care, which are indispensable for optimal outcomes and stakeholder satisfaction.

Overall, this study contributes to ongoing efforts to optimize HHC services while prioritizing environmental sustainability. By addressing current challenges and delineating avenues for future research, the study lays the groundwork for more efficient and environmentally conscious HHC operations.

9. Conclusion and perspectives

This study presents a novel environmentally friendly approach for the HHC problem. The planning process involves a two-stage model. In the first stage, a daily planning problem is formulated to design routes

for caregivers to provide care to multiple patients. This problem is modeled as a bi-objective programming model, aiming to minimize both the total travel distance and CO₂ emissions. The problem incorporates various constraints related to the HHC problem, and different versions of the NSGA-II algorithm enhanced with local search are implemented to generate Pareto solutions. The obtained solutions demonstrate that shorter routes do not always result in lower CO₂ emissions. Performance metrics are applied to assess the quality of the solutions and the efficiency of the algorithm.

In the second stage of the problem, a MILP model is introduced to balance the workloads of caregivers. This model assigns skilled caregivers to the designed patient routes. A comprehensive computational study is conducted to evaluate the proposed approach, including a comparison without considering the continuity of care.

The results indicate that all local search approaches, especially NSGA-II- α , outperform the standard NSGA-II algorithm in terms of the three performance metrics used. Although local search algorithms have higher computation times, they are still efficient, with a maximum computation time of less than 49 s for large problem instances. This demonstrates the practicality and ease of adoption of the approach for HHC services.

In conclusion, this study provides an effective solution approach for the HHC problem, considering environmental concerns. However, further research is needed to address certain limitations such as uncertainty. Uncertainty is a significant factor in HHC, and future work should focus on developing robust optimization approaches to handle real-life uncertainties related to travel time, service time, caregiver availability, and emergencies [16,67,103–107].

CRediT authorship contribution statement

Salma Makboul: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Said Kharraja:** Supervision. **Abderrahman Abbassi:** Methodology. **Ahmed El Hilali Alaoui:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

<https://github.com/SMAKBOUL/GHHC>.

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