Advances in Artificial Intelligence and Machine Learning; Research 4 (4) 3114-3124 Received 20-10-2024; Accepted 21-12-2024; Published 28-12-2024

Optimizing Healthcare Ecosystem Performance - A Computational Study of Integrated Patient Assistance in Primary Care

Francesco Nucci francesco.nucci@unisalento.it
Department of Innovation Engineering
University of Salento
Lecce, Italy

Gabriele Papadia gabriele.papadia@unisalento.it
Department of Innovation Engineering
University of Salento
Lecce, Italy

Corresponding Author: Francesco Nucci

Abstract

Home health care professionals provide medical services to patients in their homes. With rising demand, it's crucial to manage operational costs effectively while ensuring satisfaction for patients. This study presents a bi-objective optimization model aimed at resolving routing and scheduling challenges in home health care, with a focus on both system efficiency and patient accessibility. A Mixed-Integer Linear Programming Model (MILP) is developed. To tackle computational time challenges, we propose a Non-dominated Sorting Genetic Algorithm II to solve the multi-objective optimization problems. The evaluation of Pareto fronts demonstrates the method's efficiency. We apply the method in a real-world case study to provide managerial implications.

Keywords: Home health care, Bi-Objective optimization, Routing and scheduling problems

1. INTRODUCTION

Delivering medical care directly in patients' homes provides numerous advantages [1, 2]. Home-based Health Care (HHC) entails healthcare professionals visiting patients' residences to provide essential medical services and support directly in their living environments [3]. These facilities include doctor visits, delivering medications and medical supplies, collecting lab samples, managing unused medications and equipment, and maintaining equipment at home, as mentioned by [4]. Home care programs have expanded greatly to address the needs of the community [5]. This growth stems from the demonstrated efficacy of at-home care in addressing various healthcare requirements, thereby enhancing the efficiency of this approach, as shown in [6]. For instance, the study in [7] found that 81% of suggested hospital admissions were effectively managed at home, reducing the

Citation: Francesco Nucci and Gabriele Papadia. Optimizing Healthcare Ecosystem Performance - A Computational Study of Integrated Patient Assistance in Primary Care. Advances in Artificial Intelligence and Machine Learning. 2024;4(4):178

number of patients who needed hospitalization to 12% after receiving home care. Managing patients at home can reduce the costs associated with hospital stays and related expenses. Patients often prefer receiving care in the comfort of their own homes, which can lead to higher satisfaction and potentially better recovery outcomes.

According to [2], multiple studies have classified HHC into three main categories: service process, management choices, and planning timeframe. The last dimension of HHC is further divided into three levels: strategic, tactical, and operational. At the strategic level, tasks include determining facility locations, creating districts, selecting fleets, staffing, and choosing suppliers. The tactical level involves assigning fleets, scheduling shifts, allocating staff, and setting inventory policies. Finally, the operational level focuses on assigning staff, controlling inventory, and routing staff. These tasks typically encompass a mix of scheduling, resource allocation, and vehicle routing challenges, making the mathematical models used to address these issues increasingly complex. As a result, this scenario has attracted interest from researchers, policymakers, and professionals. Innovative research is vital to maintain service quality and reduce expenses given the significant demand for home health services. Scientific papers have recently addressed Integrated Care (IC) in medical studies and home care. In [8], authors explore the implementation of value-based integrated care (VBIC) and its effects on clinical outcomes, patient-reported outcomes, and healthcare utilization. It also discusses the facilitators and barriers for implementing VBIC, that are relevant in formulating a scheduling problem. In [9], a systematic review and meta-analysis seek to evaluate existing economic assessments of integrated care and examines their effects on outcomes and expenses.

Recent scientific research has addressed the vehicle routing problem (VRP) with applications in home visit scheduling, particularly focusing on healthcare scenarios. For instance, [10] examined VRPs involving synchronized visits and variable travel times, an essential aspect of home healthcare scheduling. Their work formulates the issue using a two-stage stochastic integer programming model, providing solutions for complex scenarios such as synchronized patient visits, and using advanced optimization techniques like branch-and-cut. Recent advances in the Capacitated Vehicle Routing Problem With Time Windows (CVRPTW) have employed innovative techniques like deep learning and quantum-inspired computing. These approaches have proven effective in handling large-scale VRP instances, significantly improving solution quality and computational efficiency for scheduling problems involving strict time windows [11]. The combination of machine learning and quantum computing is expected to offer even greater efficiency in the future. Some recent papers have tackled the Home Healthcare Routing And Scheduling Problem (HHCRSP) using bi-objective optimization, where the goal is often to balance competing objectives like minimizing operational costs and maximizing caregiver or patient satisfaction. In [3], the authors present a dual-objective optimization model aimed at reducing both the overall service duration and the total expenses of HHC services concurrently. Another recent paper by [12] also addresses a similar problem, proposing a bi-objective optimization model for home health care routing. This model aims to minimize travel costs and penalty costs associated with time window violations (e.g., caregivers arriving too early or too late). The model uses a Multi-Directional Local Search Algorithm embedded with Adaptive Large Neighborhood Search to handle large-scale instances of the problem. Both studies emphasize practical constraints, such as time windows, caregiver skill levels, and patient needs, which make these models suitable for real-world applications in home healthcare.

Despite the extensive literature on VRP with synchronized visits and bi-objective functions, to our knowledge, no study has simultaneously tackled both aspects within the context of the problem we examine (see next section). This article seeks to develop a new strategy that builds upon the efforts made in 2022 in [13], in response to the changing landscape of 2024. These changes are driven by the profound modifications to the healthcare system that occurred following the COVID-19 epidemic.

2. MATERIALS AND METHODS

2.1 Research Problem

This research provides an extensive and structured review of operations research models and applications in home care, concentrating on problem formulation and solution approaches. The methods explored encompass meta-heuristic algorithms and exact techniques. In our problem, the doctor must see patients in the office and provide home care for those unable to visit the medical practice (such as the elderly, disabled, or those with communicable diseases). The goal is to create a schedule for these patient requests that improve physician efficiency and respect patient time windows. The mathematical formulation of the scheduling problem is described as follows.

A list of patient requests is given (for study and home care): each request has a severity value, geographical site (physician study included), time duration and patient availability time windows (start time, end time). Constraints are driving time between locations (physician study included). The objective is getting a scheduling for the patient requests able to minimize both physician 'makespan' and patient 'total time deviation' from availability windows. In the realm of scheduling, 'makespan' indicates to the overall duration required to finish a set of tasks or jobs. Specifically, it is defined as the time that elapses from start time to the completion of the last job. Minimizing makespan is a common objective in scheduling problems, as it helps to optimize resource usage and improve efficiency. Given the fixed visit durations, reducing makespan results in shorter travel times. Parameter 'time deviation' represents the difference between the customer's desired appointment time and the actual time. It indicates the delay or advance experienced by the customer in the actual appointment schedule referring to the desired time windows. Minimizing the deviation from the time windows assigned by customers means trying to adhere as closely as possible to their requests. When comparing the articles by [3] and [12], we notice some important differences. Authors in [3] focus on minimizing time and cost, emphasizing only the financial side, while not considering service quality as we do. In [12] a more similar approach to ours is considered, aiming to reduce both travel costs and improve patient/caregiver satisfaction. Authors consider two types of time windows: a 'preferred window' when the patient requests a visit, and a broader 'strict window' during which the visit must take place. If a caregiver arrives too early, they might need to wait for the patient, and this wait affects satisfaction but is not included in travel costs. In contrast, in our model, the physician is self-employed, receiving a fixed fee from the Italian state. In many rural areas, this doctor is the only available representative of Italian healthcare system. Therefore, in emergencies, it is impossible to set narrow availability windows for patients, as they must necessarily adapt to the doctor's schedule. Nevertheless the physician must be flexible in responding to emergencies, focusing on optimizing both global visit completion time (efficiency) and patient satisfaction (quality of care). Consequently, our model differs from the approach outlined in [12].

2.2 Research Model

We modeled the described problem as bi-objective optimization. Bi-objective optimization involves simultaneously optimizing two conflicting objectives, such as efficiency and quality. This approach is particularly relevant in fields like manufacturing, logistics, and project management, where improving one aspect can often lead to a compromise in another. 'Efficiency' typically refers to maximizing output or productivity. 'Quality' focuses on meeting standards and specifications, ensuring that the final product or service is reliable and satisfactory. In our problem, efficiency is indicated by the reduction in makespan, while quality is reflected in minimizing total time deviation from patient availability window. Solutions are assessed based on Pareto optimality, meaning a solution is considered Pareto optimal if no alternative solution can enhance one objective without compromising the other. The collection of such solutions forms the Pareto front: each solution represents a different trade-off between objectives, allowing decision-makers to choose based on their preferences. To mathematically formulate the two-objective scheduling problem, we need to define the variables, constraints, and objective function. The parameters are reported as follows:

- P: Set of patients who need to be seen in their own home or at the doctor's office.
- l_i : Location of the visit for patient i, $L = \{l_i | \forall i \in P\}$.
- t_{ij} : Travel time from patient i location to patient j location.
- s_i: Severity value for patient i.
- d_i: Duration of the visit for patient i.
- b_i: Start of the time availability window for patient i.
- e_i : End of the time availability window for patient i.

Variables are listed here:

- y_i: Start time of the visit for patient i ($y_i \geq 0 \quad \forall i \in P$)
- z_i: End time of the visit for patient i
- x_{ij} : Binary variable representing whether patient j is visited directly after patient i

The constraints ensure that the physician's schedule respects the duration of each visit, and the travel time between locations. The patients' availability windows are treated as soft constraints and are included only in the objective function. Each visit has a given duration $z_i = y_i + d_i \; \forall i \in P$. The Sequence constraint states that each visit must follow the sequence dictated by x_{ij} that is: if $x_{ij} = 1$, then $z_i + t_{ij} \leq y_i \; \forall i, i \in P$. Each patient should be visited exactly once, and the sequence should ensure all patients are included:

$$\sum_{j \in P, j \neq i} x_{i,j} = 1 \quad \forall i \in P \qquad\qquad \sum_{i \in P, j \neq i} x_{i,j} = 1 \quad \forall j \in P$$

With regard to the bi-objective function, the primary goal is to minimize the makespan $\tau = \min_{i \in P}(z_i)$, while the secondary objective aims to reduce the 'total time deviation':

$$\delta = \sum_{i \in P} s_i \cdot [\max(0, b_i - y_i) + \max(0, z_i - e_i)]$$

An 'advance' is noted when the patient's visit starts before the availability window ($y_i < b_i$). Conversely, if the visit ends after the availability window closes ($z_i > e_i$) it is considered a 'delay'. In both cases, there is a 'time deviation' from the availability window. These deviations are aggregated and weighted according to the patient's severity s_i. Minimizing both τ and δ presents a conflict because reducing the makespan requires scheduling missions based on travel time, which overlooks the time windows requested by patients. Conversely, scheduling visits according to patients' preferences leads to increased travel time.

2.3 Findings

Optimization algorithms that are well-suited for solving scheduling problems in healthcare, particularly those involving minimizing makespan and time deviation are described as follows. In [14], a MILP model was developed to address staff placements, patient distributions, resource distribution, and overtime management, aiming to reduce healthcare costs and improve patient care quality. In [15], the authors use biomimicry concepts in cancer treatment to improve appointment management and therapeutic outcomes. Their study concentrates on automating this procedure using three nature-inspired algorithms: Wolf Optimization, Firefly Optimization and Genetic Algorithm.

Multi Objective Particle Swarm Optimization (MOPSO) extends the PSO algorithm to handle multiple objectives [16]. It maintains a repository of non-dominated solutions and uses a leader selection mechanism to guide the swarm. MOPSO can be used to explore the solution space and find a set of Pareto-optimal schedules. Pareto Simulated Annealing (PSA) is a variant of the SA algorithm designed for multi-objective optimization. It uses a Pareto dominance criterion to accept or reject solutions. PSA can help in finding a balance between the two objectives by exploring different scheduling configurations, see [16]. Finally, NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a commonly employed algorithm for multi-objective optimization designed to identify a set of optimal solutions. NSGA-II can be used to balance multiple objectives, such as minimizing travel time and patient visit delays, providing a set of Pareto-optimal solutions. In [16], the algorithm is utilized to tackle the scheduling model through a simulation-based approach. Finally, these algorithms offer various approaches to tackle the scheduling problem, each with its strengths and suitable applications.

To effectively reduce the Pareto front to the most relevant solutions, a Convex Hull-Based Multi-objective optimization approach is utilized. The convex hull refers to the smallest convex set that encloses a given set of points. In the context of multi-objective optimization, it serves as an approximation of the Pareto front, which showcases the optimal trade-offs between competing objectives. Several algorithms, such as [17] and [18], have been designed using convex hull-based sorting and selection methods to efficiently approximate optimal solutions. Convex hull-based strategies can outperform traditional multi-objective optimization techniques by focusing on the most advantageous regions of the solution space, providing a more accurate approximation of the Pareto front.

Algorithm 1 Crowding Distance Calculation Algorithm

Require: Population of solutions Ψ of size N, $M = 2$ objective functions $f_1 = \tau$, $f_2 = \delta$
Ensure: Crowding distance c_i for each solution i in the population

```
Initialize: For each solution i ∈ Ψ, set c_i = 0
for each objective m from 1 to M do
    Sort population Ψ in ascending order based on f_m
    Assign c_first = ∞ and c_last = ∞ to the boundary solutions
    for each solution i where 1 < i < N do
        Compute the crowding distance for solution i: c_i = c_i + (f_m(i+1) − f_m(i−1)) / (f_m^max − f_m^min)
        where f_m(i+1) and f_m(i−1) are the values of the neighboring solutions, and f_m^max, f_m^min
        are the maximum and minimum objective values in the population.
    end for
end for
return Crowding distances c_i for all solutions in the population
```

We implemented an NSGA-II algorithm to address the described multi-faceted optimization challenge, incorporating a convex hull-based strategy. The key components of NSGA-II algorithm include:

- Solution Encoding. The representation of candidate solutions consists of the patient visit sequence
- Population Initialization. The initial set of solutions (population) is randomly generated with 3 rules randomly selected. The first rule is fully random. The second one selects the next patient on the basis of the travel distance from the previously visited patient (starting from doctor office). The last rule choose the next patient on the basis of their availability windows.
- Non-dominated Sorting. The ranking mechanism sorts the population into various layers according to Pareto dominance based on makespan τ and total deviation δ.
- Crowding Distance Calculation. To maintain diversity within the population we estimate the density of individuals around a given solution using ALGORITHM 1.
- Selection. We use tournament selection to choose solutions based on their rank (from non-dominated sorting) and crowding distance, giving preference to those with higher ranks and larger crowding distances.
- Crossover. We employ a 2-point crossover operator, which merges two parent solutions to generate offspring, enhancing the exploration of the solution space.
- Mutation. Randomly selecting and swapping two elements in the patient visit sequence introduces diversity and helps prevent premature convergence.
- Termination Criteria. The algorithm stops upon reaching a specified count of generations.

i	l_i	s_i	d_i (mins)	b_i	e_i
1	0	1	30	0	300
2	0	2	30	40	150
3	0	1	45	80	380
4	1	2	60	0	120
5	2	1	30	180	350
6	3	2	45	120	250

Table 1: Patients

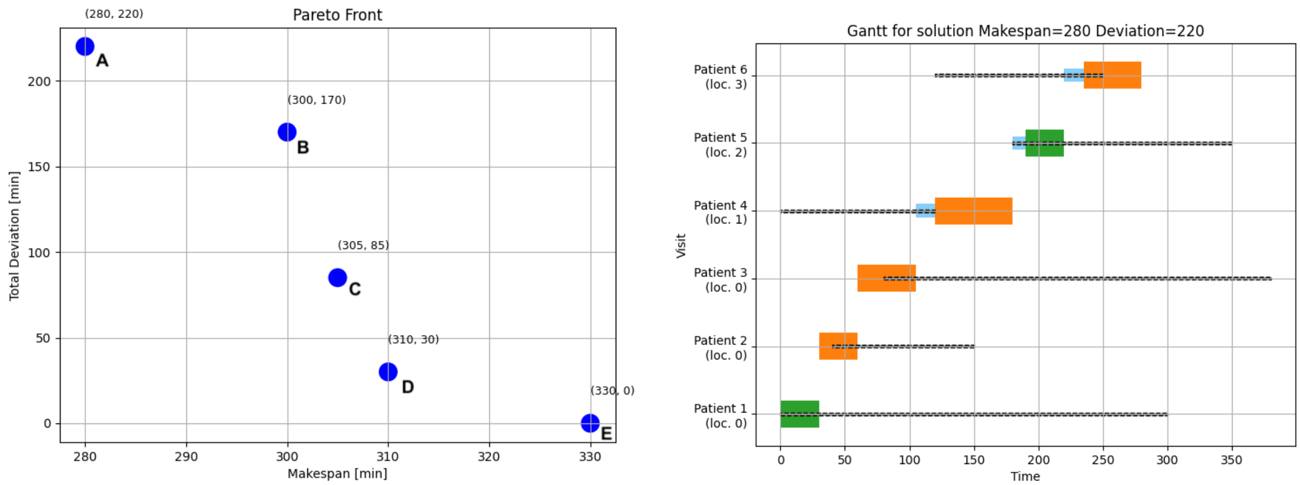
Locations From / To	0 (patients 1,2,3)	1 (patient 4)	2 (patient 5)	3 (patient 6)
0 (patients 1,2,3)	-	15	20	25
1 (patient 4)	15	-	10	30
2 (patient 5)	20	10	-	15
3 (patient 6)	25	30	15	-

Table 2: Location travel time matrix (mins)

3. RESULTS

In this section, we will first illustrate with a simple example how our method works. The data on the patients are shown in TABLE 1. As can be seen, three patients are received in the doctor's office (location 0), while the other three are visited in their homes (locations 1,2,3). The duration of the visits is between 30 minutes and one hour. The width of patients' availability windows varies greatly, noting that those with greater severity unfortunately have less availability. The travel time matrix is shown in TABLE 2. The shortest route to visit all locations, starting from the physician's study, is $0 \to 1 \to 2 \to 3$ with a total travel time of $15 + 10 + 15 = 40$ min.

After running the algorithm, we obtained the Pareto optimal solution set shown in FIGURE 1a, which includes all the identified optimal solutions. Solutions A=(280,220) and E=(330,0) each focus on optimizing only one parameter, which causes the other parameter to have an unacceptable value. Solution D=(310,30) appears to be the most relevant: compared to Solution E with an increase of just 30 minutes in total deviation, it achieves a 20-minute reduction in makespan. In contrast, solutions B=(300,170) and C=(305,85) offer only minor makespan savings but cause a significant increase in the total deviation parameter. To support the physician in choosing the best scheduling of appointments, we generate the Gantt chart for solution A, E and D, see FIGURE 1b and FIGURE 2. In the Gantt chart, the activities are colored green or orange depending on whether they meet their respective availability windows (highlighted with a dashed line). The travel between the previous location and the current one is shown in light blue. FIGURE 1b presents the Gantt chart for Solution A, which focuses solely on minimizing the makespan. As a result, the doctor follows the shortest path (locations 0-1-2-3). However, the visits to patients 2 and 3 are completed earlier than requested, leading to a deviation. The doctor then travels to patient 4's location, where the visit is performed late. The visit to patient 5 is conducted on time, according to their request. Finally, the doctor visits patient 6, but this visit is also completed late. As a result, the total deviation value is significantly high, mainly because the visits to critical patients 2, 4, and 6 are delayed, and these delays are penalized at twice the standard rate. In FIGURE 2a, the Gantt chart illustrates solution E, which



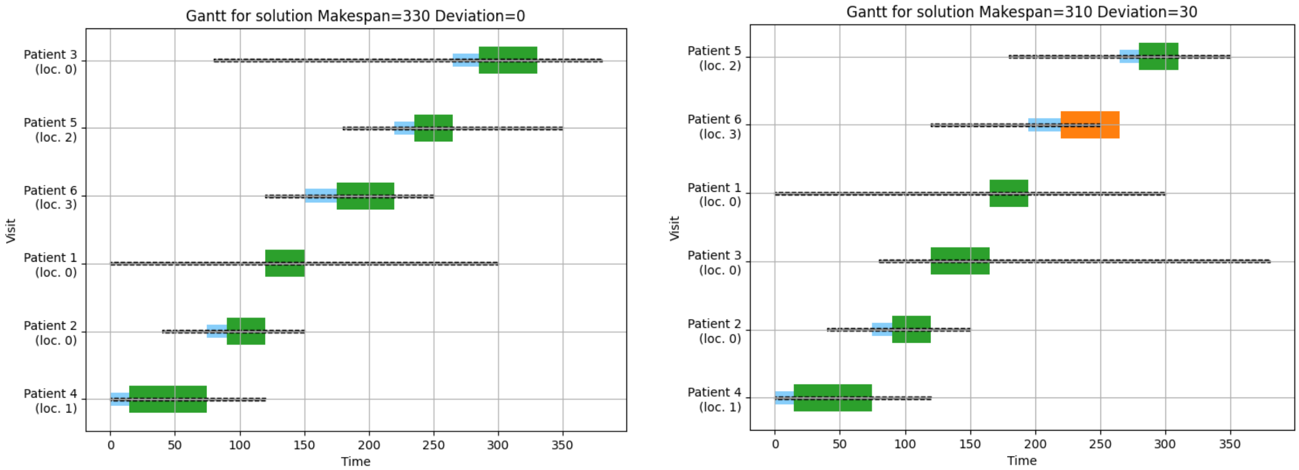
(a) *(b)*

Figure 1: Example - Pareto optimal solution set and Gantt for solution A=(280,220)

mainly focuses on minimizing the total deviation. The physician schedules appointments based on the patients' availability, extending the travel route (locations 1-0-3-2-0). The physician first visits patient 4 at their home. Afterward, they return to the study to see patients 2 and 1. Following these, the doctor travels to patient 6, then to patient 5. Finally, the physician returns to the clinic to see patient 3. This leads to an increase of 50 minutes in the makespan, due to the additional travel, compared to solution A. In FIGURE 2b, the schedule of the solution D that best optimizes both objectives is shown. The physician begins by visiting patient 4 at their home. Then, they return to the clinic to see patients 2, 3, and 1. Afterward, the physician visits patient 6, finishing the appointment later than requested. Finally, they conduct a home visit for patient 5 as scheduled. Compared to solution A, this solution includes an additional initial trip, but only patient 6 falls outside the availability windows.

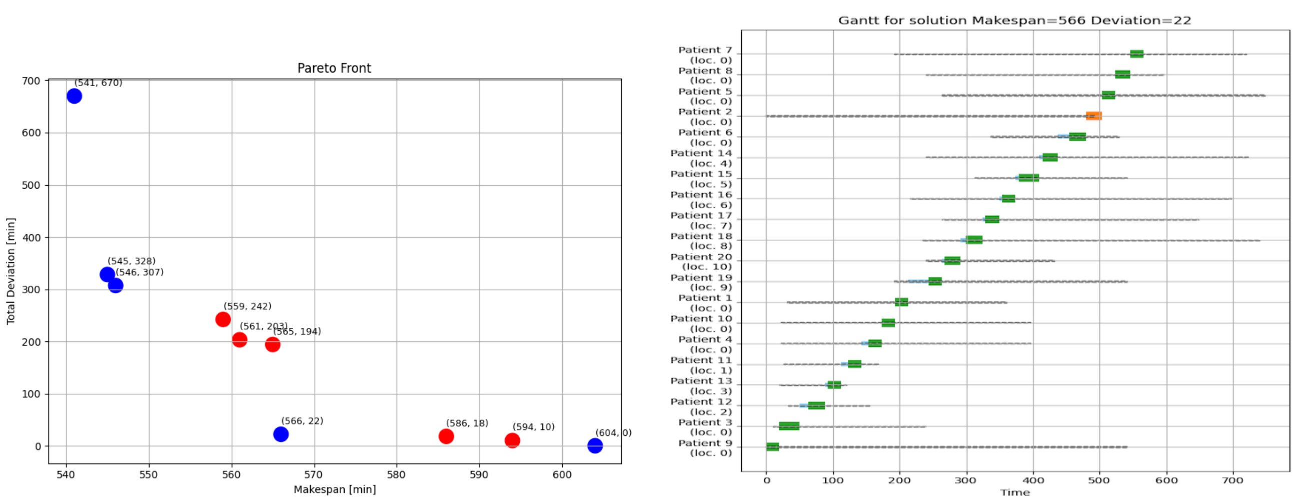
Finally, we considered the case study file referenced in [19], which presents a real scenario where a doctor manages 20 patients—half receiving care in the office and the other half at home. The duration of each visit ranges from 20 to 30 minutes. Statistical insights into travel times reveal the following: mean travel time 13.36 minutes, minimum 5 minutes, and maximum 33 minutes. Additionally, the ratio between the width of the patient's availability window and the length of the time horizon provides information on how little the patients impose constraints on the doctor. Higher ratios suggest that patients are more flexible and impose fewer constraints on the doctor's schedule. In the case study, we have: mean ratio 8.6%, minimum ratio 5.7%, and maximum ratio 12.5%. After a tuning phase, we selected the parameters for the NSGA-II algorithm: a population size of 100 individuals, 100 parents selected for breeding per generation, 200 offspring generated per generation, a mutation probability equal to 0.3, a crossover probability equal to 0.7, and 50 generations for the algorithm run.

Upon executing the algorithm, we derived the Pareto optimal solution set depicted in the FIGURE 3a. The blue solutions are part of the convex hull, while the red solutions are not. Notably, the solutions within the convex hull are the most significant. Among these, the solution (566, 22) stands out. Compared to the solution that primarily optimizes the total deviation parameter (604, 0),



(a) *(b)*

Figure 2: Example - Gantt for solution E=(330,0) and solution D=(310,30)



(a) *(b)*

Figure 3: Case Study - Pareto optimal solution set and Gantt for solution A=(566,22)

it achieves a substantial reduction in makespan—from 604 to 566 min—while maintaining a very low total deviation of 22 min. In contrast, the solutions on the left side reduce the makespan by about 20 min but result in a significant increase in total deviation, exceeding 300 min. Gantt chart for the solution (566, 22) is displayed in FIGURE 3b.

As this study relies on actual data supplied by a practicing physician, the doctor reviewed the results of the Pareto front and confirmed that the solutions on the convex hull were the most significant. Of these, the doctor identified the solution (566,22) as the best representation of the optimal balance between the two objectives.

4. CONCLUSIONS

We created a bi-objective model for the HHC issue, aiming to optimize both makespan and patient satisfaction while considering patient time windows and travel times. To address this bi-objective optimization challenge, we employed an NSGA-II algorithm to generate Pareto fronts. A comparison between the ILOG CPLEX Solver and NSGA-II demonstrated the latter's enhanced effectiveness and ability to produce good solutions.

In a real-world case study, a practicing physician validated that the NSGA-II's best solution was the most significant. The growing demographic of elderly individuals, coupled with the decline in working-age populations, highlights the increasing necessity to enhance the use of home care services.

Home care not only offers a patient-centered approach that improves the quality of life for older adults by allowing them to maintain independence and remain in familiar surroundings, but it also alleviates pressure on hospital and long-term care facilities, helping to reduce healthcare system overloads. Moreover, expanding home care services can optimize resource allocation by reducing the demand for costly inpatient care while allowing healthcare providers to manage chronic conditions more efficiently through regular monitoring and preventive interventions.

For future work, we plan to develop new heuristics and introduce uncertainty into the problem data. Additionally, more applicable goals and limitations, driven by the requirements of HHC physicians, may be integrated in future research.

References

[1] Braekers K, Hartl RF, Parragh SN, Tricoire F. A Bi-objective Home Care Scheduling Problem: Analyzing the Trade-off Between Costs and Client Inconvenience. European J Oper Res. 2016;248:428-443.

[2] Goodarzian F, Garjan HS, Ghasemi P. A State-Of-The-Art Review of Operation Research Models and Applications in Home Healthcare. Healthcare Analytics. 2023;4:100228.

[3] Goodarzian F, Abraham A, Fathollahi-Fard AM. A Biobjective Home Health Care Logistics Considering the Working Time and Route Balancing: A Self-Adaptive Social Engineering Optimizer. Journal of Computational Design and Engineering. 2021;8:452-474.

[4] Grenouilleau F, Legrain A, Lahrichi N, Rousseau LM. A Set Partitioning Heuristic for the Home Health Care Routing and Scheduling Problem. European Journal of Operational Research. 2019;275:295-303.

[5] Goodarzian F, Abraham A, Ghasemi P, Mascolo MD, Nasseri H. Designing a Green Home Healthcare Network Using Grey Flexible Linear Programming: Heuristic Approaches. J Comput Des Eng. 2021;8:1468-1498.

[6] Demirbilek M, Branke J, Strauss A. Dynamically Accepting and Scheduling Patients for Home Healthcare. Health care management science. 2019;22:140-55.

[7] Tanoumand N, Ünlüyurt T. An Exact Algorithm for the Resource Constrained Home Health Care Vehicle Routing Problem. Annals of Operations Research. 2021;304:397-425.

[8] Gonzalez SJ, Mejia de Grubb MC, Zoorob RJ. Patient-Centered Medical Home and Integrated Care in the United States: An Opportunity to Maximize Delivery of Primary Care. Family Medicine and Community Health. 2015;3:48-53.

[9] Rocks S, Berntson D, Gil-Salmerón A, Kadu M, Ehrenberg N, et al. Cost and Effects of Integrated Care: A Systematic Literature Review and Meta-Analysis. The European Journal of Health Economics. 2020;21:1211-1221.

[10] Hashemi Doulabi H, Pesant G, Rousseau LM. Vehicle Routing Problems With Synchronized Visits and Stochastic Travel and Service Times: Applications in Healthcare. Transportation Science. 2020;54:1053-1072.

[11] Dornemann J. Solving the Capacitated Vehicle Routing Problem With Time Windows via Graph Convolutional Network Assisted Tree Search and Quantum-Inspired Computing. Frontiers in applied mathematics and statistics. 2023;9:1155356.

[12] Zhao J, Wang T, Monteiro T. A Bi-objective Home Health Care Routing and Scheduling Problem Under Uncertainty. International Journal of Environmental Research and Public Health. 2024;21:377.

[13] Secundo G, Nucci F, Shams R, Albergo F. Optimising Workforce Efficiency in Healthcare During the COVID-19: A Computational Study of Vehicle Routeing Method for Homebound Vaccination. Production Planning & Control. 2024;35:1593-1607.

[14] Yinusa A, Faezipour M. Optimizing Healthcare Delivery: A Model for Staffing, Patient Assignment, and Resource Allocation. Applied System Innovation. 2023;6:78.

[15] Keshav Kumar K, Narasimham NVSL, PA Ramakrishna. Biomimicry in Radiation Therapy: Optimizing Patient Scheduling for Improved Treatment Outcomes. Advances in Artificial Intelligence and Machine Learning. 2024;4:2452–2467,

[16] Ala A, Alsaadi FE, Ahmadi M, Mirjalili S. Optimization of an Appointment Scheduling Problem for Healthcare Systems Based on the Quality of Fairness Service Using Whale Optimization Algorithm and NSGA-II. Scientific Reports. 2021;11:19816.

[17] Wang P, Emmerich M, Li R, Tang K, Bäck T, et. al. Convex Hull-Based Multiobjective Genetic Programming for Maximizing Receiver Operating Characteristic Performance. IEEE Transactions on Evolutionary Computation. 2015;19:188-200.

[18] Hong W, Tang K. Convex Hull-Based Multi-Objective Evolutionary Computation for Maximizing Receiver Operating Characteristics Performance. Memetic Computing. 2016;8:35-44.

[19] https://github.com/fnuni/2024aaiml/blob/main/configuration20github.json.