Addressing Delays and Earliness in Home Health Care Routing and Scheduling Problems

By

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Abstract

Optimized Routing and Scheduling (RS) for mobile caregivers is essential for the efficient management of Home Health Care services. Unexpected events, such as traffic jams and visits lasting longer or shorter than expected, may affect the initial caregiver's schedule by delaying or accelerating visits. Therefore, the RS should be continuously updated to deliver services that respect the problem constraints, e.g., patients' and caregivers' availability, caregivers' breaks, etc., while minimizing the total costs of services. The services costs include travel, overtime, time exceeding patient time windows, and working time differences among caregivers. In this research, we formulate and solve a mixed-integer linear programming RS model that considers delays and earliness throughout the day. Once delays or earliness arise, we propose a rescheduling approach capable of updating the current schedule to consider the time difference and instantly provide a new optimal outcome. Results show a decrease in total costs in 48% of the cases, with an average saving of 349$ per day when rescheduling patients. 15% of the cases present an increase in total costs by an average of 143$ per day. No change is observed in 37% of the cases. Finally, when applying the rescheduling approach, results show that larger time windows provide more significant savings when delays are observed throughout the day.

Contents

List of Figures

List of Tables

1. Introduction

The **Home Health Care** (HHC) industry provides nursing, personal support and therapy to help people in need live independently at home (Government of Canada, 2016). As the population is aging, health care workers, such as nurses, physicians, social workers, caregivers, etc., are increasingly required to provide care to patients in their houses (Di Mascolo et al., 2021; Government of Canada, 2004). HHC offers many benefits, for example; it frees beds in hospitals to make space for people who really need to be there and it reduces overall care costs since patients are at home and do not require 24/7 attention from a medical team (Cissé et al., 2017; Di Mascolo et al., 2021). Typical patients who receive home care services are those with chronic illnesses such as diabetes, chronic obstructive pulmonary disease, cancer, and those in rehabilitation (Paltser et al., 2020). According to Paltser et al. (2020):

"*From 2017 to 2018, a total of 351,456 hospital patients in Canada were discharged with a recommendation for formal home care. Every day, on average, 1,320 patients occupying Canadian hospital beds are waiting for home care services to be ready – the equivalent of three large hospitals filled to capacity.*"

Furthermore, the Canadian Medical Association (2021) projects an increase in demand of 53% for HHC services by 2031. Despite this rising demand, they estimate cost savings of $794 million by 2031 by shifting from long-term care homes to home care (Canadian Medical Association, 2021). Hence, HHC services are an effective way forward to provide care to people in need while reducing overall costs.

For efficient management of HHC services, optimized Routing and Scheduling (RS) for mobile health care workers, hereafter referred to as caregivers, while considering patients' schedules, visits' duration, and caregivers' breaks, among other aspects of the problem, is essential (Fikar and Hirsch, 2016). Caregivers need to travel between patients' appointments. However, complying with care schedules when one has to move between different locations for appointments is challenging. Some unexpected events can affect the original caregivers' schedule by delaying or accelerating some visits during the day:

- A physiotherapy treatment might have lasted longer than expected due to the patient's condition on that day,

- The blood collection performed by the nurse might have been easier that day; hence the visit was shorter than expected,
- There might have been traffic jams or accidents on the road, leading the appointment to start late and finish later than expected.

Being late can substantially disturb daily schedules. An appointment taking less time than expected might also affect the program, giving the caregiver flexibility to change the order in which patients are seen throughout the day to meet the ideal routing. In either case, being late or ahead of schedule, the current RS is no longer optimal, and it can impact the overall costs and patients' and caregivers' satisfaction (Panagiotoglou et al., 2017). Therefore, it is essential to update the RS of visits in the case of uncertainties due to delays or opportunities to deliver services earlier (earliness) when possible.

This thesis proposes a rescheduling approach to ensure that caregivers' RS are constantly optimized during home care services delivery when they face delays or early visit completion. Hence, we approach the Home Health Care Routing and Scheduling Problem (HHCRSP) from a mathematical optimization perspective. Obtaining the updated RS can be done by re-optimizing the previous one considering the different delays or opportunities observed during a caregiver's workday while still considering care constraints. The goal is to minimize the total costs when delays or earliness arise throughout the day while respecting the different problem constraints. We aim to minimize the total costs of travel time between locations and the total costs of overtime from the caregiver, maximize patients' satisfaction by respecting as much as possible their time windows, and maximize a workload balance across caregivers by minimizing the working time difference between them. Organizations working with multiple caregivers with similar working skills and seeing numerous patients throughout the day could benefit from a rescheduling approach, as seeing many patients daily increases the chances of delays and earliness. Also, organizations that are seeing patients with small appointment durations would be the ones benefiting from this type of solution, as they are the ones who might see multiple patients per day.

This thesis considers the problem as a two steps optimization problem. HHCRSP-1 represents the first optimization problem to solve, and HHCRSP-2 is the second. In the first optimization, we assign all patients that need to be visited daily to a working caregiver to find the initial schedule. In this first step, the HHCRSP-1 can be considered a variation of the Vehicle Routing Problem with Time Windows (VRPTW) (Begur et al., 1997) since we assume multiple caregivers are available daily. Hence, we formulate the HHCRSP-1 as a Mixed-Integer Linear Programming (MILP) model. Once all patients are assigned to a caregiver, the HHCRSP-2 can be considered a variation of the Traveling Salesman Problem with Time Windows (TSPTW) since we consider only one caregiver at the time (Dantzig & Ramser, 1959; Kumar & Panneerselvam, 2012). Dantzig & Ramser (1959) consider the Vehicle Routing Problem (VRP) an extension of the Traveling Salesman Problem (TSP); hence we also formulate the HHCRSP-2 as a MILP model.

As this thesis focuses on the rescheduling approach, we use the commercial solver CPLEX to solve both models. According to IBM (2022), CPLEX has shown great efficiency in quickly solving small instances for MILP problems. In Irani et al. (2018)'s study, caregivers visit, on average, seven patients per day (eight-hour shifts), depending on the length of visits and the location of patients. Thus, the CPLEX solver enables us to apply the rescheduling approach to small instances. The scenarios, which represent one caregiver per day, tested and analyzed show a decrease in total costs in 48.38% of the cases (150 cases with an average saving of 349$) when the rescheduling approach is applied. In 36.45% of the cases (113 cases), no change in total costs is observed when rescheduling patients. Finally, there is an increase in total costs in 15.16% of the cases (47 cases with an average of 143$ per scenario) when rescheduling patients. Overall, we observe total costs decrease by 14%, representing a saving of 147$ per scenario on average. The results also show that larger time windows enable more significant savings than smaller ones. When applying the rescheduling approach, we observe a total cost difference of 51% (an average of 457$ difference) between three-hour time windows and five-hour time windows.

The rest of the manuscript is organized as follows. Section 2 presents the relevant literature. Section 3 and 4 provide the problem description and the research questions, respectively. Section 5 presents the mathematical models, and Section 6 analyses and discusses the results. Finally, we discuss our findings and the future considerations in Section 7.

2. Literature Review

The Home Health Care Routing and Scheduling Problem (HHCRSP) is a known combinatorial problem that has been studied for years (Di Mascolo et al., 2021). This optimization problem is an extension of the Vehicle Routing Problem with Time Windows (VRPTW), which is a strongly NP-hard problem (Begur et al., 1997; Solomon & Derosiers, 1988). According to Cissé et al. (2017)

*"The **home health care routing and scheduling** problem consists of designing a set of routes used by care workers to provide care to patients who live in the same geographic area and who must be treated at home."*

With its complexity and specific side constraints, the HHCRSP has interested many researchers in the world of Operations Research (Milburn, 2012). Fikar and Hirsch (2017), Cissé et al. (2017), Grieco et al. (2021), and Di Mascolo et al. (2021) all have published important literature reviews on the HHCRSP and its variants. Their meta-analyses compare research contributions and provide insight into HHC optimization problems. The principal modelling approaches for the HHCRSP are based on mathematical programming, particularly MILP models (Di Mascolo et al., 2021). On top of MILP, integer linear programming and mixed-integer programming models, researchers have also proposed constraint programming models (Hiermann et al., 2015), cardinality-constrained approach (Carello & Lanzarone, 2014), stochastic programming models (Yuan et al., 2018) and multi-agent approaches (Marcon et al., 2017) to address this problem. All present benefits and challenges in their implementation, depending on the constraints and the solution methods applied. The main solution methods presented in the literature are metaheuristic methods (Fikar & Hirsch, 2018; Lin et al., 2018; Moussavi et al., 2019; Yuan & Jiang, 2017) and exact methods (Wirnitzer et al., 2016; Yuan et al., 2015), which includes the utilization of commercial solvers such as IBM ILOG CPLEX (Carello et al., 2018) and Gurobi (Kandakoglu et al., 2020). The solution approach chosen mostly depends on the settings, the size of the problem, the constraints and objectives, and the speed and quality of the solution found (Fikar & Hirsch, 2017). In our case, we are solving the problem as a variant of the VRP and TSP (HHCRSP-1 and HHCRSP-2, respectively) for small instances where exact methods, especially commercial solvers, have shown great efficiency (Cissé et al., 2017; IBM, 2022). Furthermore, studies either focus on a single-period planning horizon (e.g. Yuan et al., 2015) or a multi-period planning horizon, which can be multiple days (e.g. Lin et al., 2018) or multiple weeks (e.g. Carello et al., 2018).

Section 2.1 presents the main objective functions considered in the HHCRSP, and Section 2.2 introduces the principal constraints for this problem. Finally, Section 2.3 brings up the main challenges observed in the literature when addressing the HHCRSP.

2.1 Objective Functions in HHCRSP

Papers on this topic are often compared based on the objective function proposed. The main objectives studied in HHC optimization problems are minimizing costs such as route costs (e.g. travel costs) and staff member costs (e.g. overtime costs) (Di Mascolo et al., 2021; Fikar & Hirsch, 2017; Grieco et al., 2021). The second category of objective function criteria concerns patients and staff preferences. According to the literature review from Di Mascolo et al. (2021), maximizing patient preferences (e.g. minimize time windows violation) (Decerle et al., 2018-A; Hiermann et al., 2015) and maximizing staff member preferences (e.g. maximize a balanced workload) (Carello et al., 2018; Decerle et al., 2019) are considered in many HHCRSP papers. The mentioned preference criteria are critical when wanting to improve the quality of HHC services.

In the HHCRSP, most papers include at least two objective criteria, usually combined as a weighted sum of the corresponding objective functions (Decerle et al., 2019; Kandakoglu et al., 2020; Rest & Hirsch, 2016; Yuan et al., 2015). The combination of criteria varies and depends on the organizations and their objective (Cissé et al., 2017). As Cissé et al. (2017) mentioned, the HHCRSP is often modelled based on an extension of existing models (e.g. VRP (Dantzig & Ramser, 1959), VRPTW (Solomon, 1987), TSP (Flood, 1956), etc.) to which we add specific care constraints. The variety of contexts in which models have been developed explains the diversity of models. The models are customized to the particular context for which they are designed. Indeed, the type of infrastructures, the patients' and caregivers' types and preferences differ from one country, region or institution to another.

2.2 Constraints in HHCRSP

According to Di Mascolo et al. (2021), the main constraints included in HHCRSP are temporal constraints, which consider patients' and caregivers' time windows (Decerle et al., 2019; Hiermann et al., 2015; Rest & Hirsch, 2016). Patients and staff have different availability due to preferences and/or care constraints; hence, including time windows is usually essential. The second most popular category of constraints is assignment constraints, including qualification requirements (Carello et al., 2018; Lin et al., 2018) and continuity of care (Demirbilek et al., 2019; Wirnitzer et al., 2016). Our model will include time windows but exclude qualification requirements since all workers have the required skill set to treat all patients. It will also exclude constraints for continuity of care, as, in this study, we solve the problem for small instances (only two or three caregivers at a time). Having these sets of constraints would limit the effectiveness of our approach. In future work, continuity of care could be included when solving bigger instances.

2.2.1 Soft vs. Hard Time Windows

Most studies consider patient time windows, i.e., periods of time during which patients are available to receive home care (Cissé et al., 2017). There are two types of time windows: hard/fixed (Carello et al., 2018; Lin et al., 2018) and soft/flexible (Decerle et al., 2018-A; Yuan & Jiang, 2017). In the first case, the decision-maker is constrained to plan the visit within the specified time frame. In the second case, time windows can be violated, and delays can be tolerated, but with a penalty (Cissé et al., 2017). Soft time windows are introduced, in many cases, to incorporate patients' preferences (Fikar & Hirsch, 2017). When soft time windows are not satisfied, it is penalized. Many directly introduce a penalty in the objective function. Decerle et al. (2018-A) propose a pricewise-linear penalty function to disincentivize earliness or delays at the appointment's start. Du et al. (2019) introduce a term in the objective function to maximize patient satisfaction by penalizing delays with respect to the preferred time windows. Di Mascolo et al. (2021) and Cissé et al. (2017) highlight that more studies considering different types of time windows need to be performed.

2.2.2 Length of Time Windows

Although RS problems with time windows have been studied by many, only a few focus on the impact of the length of time windows (Budak & Chen, 2020). Budak & Chen (2020) analyzed the effect of the length of time windows on delivery operations for the Travelling Salesman Problem with Time Windows (TSPTW). Their results show that increasing the length of time windows decreases tour duration and clients' satisfaction, and it increases solution time. On the other hand, decreasing the length of time windows increases tour duration and clients' satisfaction and reduces solution time (Budak & Chen, 2020). Ouertani et al. (2019) tested their solution approach for the Dynamic Home Health Care Routing Problem (D-HHCRP) and performed an analysis on the instances from Solomon's 100-customer benchmark problems (Solomon, 1987), where instances with short and large time windows are compared. Instances with wider time windows have better solution results, i.e., less travel time, than those with smaller ones. The same conclusion was observed by Hong (2012) and De Armas & Melián-Batista (2015).

In the HHC context, the length of the time windows can impact patient satisfaction as well as the cost of services. Braekers et al. (2016) analyzed the trade-off between costs and client inconvenience. Their conclusion mentioned that the smaller the length of time windows, the more costly it is to offer the same service level (Braekers et al., 2016). To the best of our knowledge, they are the only ones who analyzed the impact of different lengths of time windows for the HHCRSP.

2.3 Challenges in HHCRSP

The HHC industry faces many challenges based on the unpredictability of delivering care in the home health environment. Unforeseen events often disrupt planned schedules (Visentini et al., 2014). This includes challenges in modifying the schedules based on patients' requirements and staff availabilities, expecting more extended visits, and preserving continuity of care with patients (Irani et al., 2018). Service interruptions can result in higher expenditures and reduced service quality (Visentini et al., 2014). Di Mascolo et al. (2021) categorize uncertainties related to HHCRSP into three categories: (1) changes related to demands, i.e., only one visit or one type of visit is affected by the changes (e.g., changes in travel times (Yuan et al., 2018)), (2) changes related to patients, i.e., all visits with the same patient are affected by the changes (e.g., new patients in the system (Demirbilek et al., 2019)), and (3) changes related to staff members (e.g., a caregiver going on sick leave or changing their availabilities during the planning horizon (Xie & Wang, 2017)).

Du et al. (2019), Yuan & Jiang (2017), and Kandakoglu et al. (2020) consider unexpected events, such as cancellations of visits and urgent patients added. Du et al. (2019) minimize travel time and visit duration (e.g., the turnaround time of caregiver) and maximize patients' satisfaction. Their patient satisfaction function considers the latest time a visit can start and the actual start of the appointment. Once an unexpected event happens, they launch the model to reschedule the remaining patients. Although they consider unforeseen events in their paper, they do not consider the workload distribution among care workers. They mention a significant difference in nurses' workload with their approach. Yuan & Jiang (2017) introduce disruption management for the real-time HHCRSP. Patients' appointments can not start before their earliest available start time but may commence after their latest start time at a penalty cost. They minimize travel and penalty costs for late arrivals at patients' homes. They aim to adjust the original schedule to reduce the impact of disturbances due to unexpected events on the caregivers, patients, and companies. Kandakoglu et al. (2020) propose having floating nurses called on short notice to deal with emergencies. In HHCRSP, correcting a schedule on an operational level once disturbances have occurred has not received much attention yet (Di Mascolo et al., 2021).

2.3.1 Unexpected Events in the Transport Industry

Unexpected events arise in the transport industry too. New requests, cancellations, vehicle breakdowns, supply delays and traffic can impact the quality of services (Li et al., 2009; Ritzinger et al., 2016; Wu et al., 2020). Visentini et al. (2014) review methods used in real-time vehicle schedule recovery in transportation services when facing unexpected events. They identify three main strategies in the rescheduling process: (1) dynamic, (2) predictive, and (3) reactive. The dynamic strategy offers quick solutions, usually provided by humans when disturbances arise. Predictive methods are applied within a robust scheduling context; the probability distributions of possible disruptions and scenarios are assumed to be known in advance. Finally, reactive strategies are applied once unexpected events arise. A new schedule is proposed based on accurate monitoring of the resources involved (Visentini et al., 2014). Our interest is in reactive strategies as they are dealing with unexpected delays. Li et al. (2009) present an approach to solving the Vehicle Rescheduling Problem (VRSP) where they minimize a weighted sum of different functions, including minimizing the number of changes from the initial schedule. They mentioned their approach is more efficient when no other vehicles are available at the depot to replace those that break down (Li et al., 2009). Wu et al. (2020) propose a disruption recovery model for perishable food delivery based on the disruption management theory, introduced by Yu and Qi (2004), to minimize the negative effects of deviating from the initial schedule on the participants (customers, drivers, and company). Their solution approach reschedules the following customers based on priority levels while minimizing disturbances from the initial schedule. In the transport industry, many consider having another vehicle available at the depot in case of major unexpected events (Visentini et al., 2014).

The literature reviews by Di Mascolo (2021) and Cissé et al. (2017) on HHCRSP suggest the field could move forward by addressing different types of time windows and the uncertainties in the day-to-day operations in the HHCRSP. According to Visentini et al. (2014), real-time vehicle recovery research in the transport industry still has much more to discover, and a focus on passenger preferences should be considered. This thesis fits into the body of knowledge by covering these three different aspects: (1) different time windows, (2) daily delays, and (3) patients' preferences for the HHCRSP.

3. Problem Description

The HHCRSP can be solved using Operations Research techniques to ensure optimal or feasible RS for caregivers (Milburn, 2012). In this problem, caregivers provide care to a set of patients in need of treatment in their homes. The list of patients needing care, their locations, and the number of working caregivers are known for a specific day. Thus, we want to assign patients to caregivers in the most efficient way. This problem is then complicated by patients' care constraints, involving appointment durations and time windows to receive care (Milburn, 2012). In order to formulate the problem mathematically, we make the following assumptions:

- Caregivers start and finish their day at the medical centre,
- All caregivers have the required skills to treat all patients,
- All patients are only being visited once a day,
- Caregivers work for multiple hours a day (full day),
- Caregivers are allowed a lunch break within a determined time interval,
- Patients' time windows can be violated (only late arrivals are allowed) but at a penalty cost.

The assignment of patients to caregivers is based on minimizing the total costs of services. The total costs come from four sources: (1) the travel time between locations, (2) the overtime for each caregiver, (3) exceeding patients' time windows (maximize patient satisfaction) and (4) working time difference among caregivers (workload imbalance). This HHCRSP is considered a variant of the VRPTW (Begur et al., 1997). Hence, it can be formulated as a MILP model. Once this HHCRSP is solved, using the commercial solver CPLEX, each caregiver receives the list of patients they need to see throughout the day and their RS. On the list, they can see the sequence of patients, each appointment's starting time and duration, the expected travel time between the different locations and their lunch break time.

Starting at the medical centre, each caregiver takes the specific medications required by the patients on their list and the equipment needed for the appointments. Each caregiver then leaves the medical centre to visit the first patient on their list. Once the appointment is completed, it might be earlier or later than expected with respect to the original schedule; there could have been traffic on the road that led to starting the appointment later, or the visit took longer than expected. Thus, the initial schedule is no longer valid due to time uncertainties. In addition, accumulated delays or earliness throughout the day can impact the total costs of services. Due to long delays, subsequent patients might not receive their treatment on time, and the caregivers might need to stay longer to visit all patients. Shorter appointments might also impact the RS by reducing travel time or overtime. There could be opportunities to visit some patients earlier than expected without arriving before their earliest availability. Patients are expected to be seen during their time windows, but they do not know precisely when the caregiver will come. Hence, it is possible to change the caregiver's schedule by seeing patients earlier than they were initially supposed to and respecting their time windows. Therefore, caregivers' RS could be revised in order to cover those delays and earliness happening daily.

4. Research Questions

Many questions emerged from the above problematic situation. Our first research question goes as follows:

How can we ensure optimal rerouting and rescheduling for caregivers delivering home health care services when they face delays and earliness during their workday?

The original schedule is no longer valid once there are delays and/or earliness throughout the day. Hence, we propose rescheduling patients after each visit to ensure the time difference with the original schedule is considered in the next RS. The proposed rescheduling approach is a reactive approach as we suggest rescheduling patients once the delay or earliness has happened. We propose this approach because the delays and earliness are uncertain and can vary daily.

Therefore, a predictive approach would necessitate greater knowledge of those possible uncertainties, which are not considered in this study.

In this rescheduling process, we consider one caregiver at a time since they have the medical equipment and medications to treat the patients on their list only. Thus, we propose a rescheduling approach based on the HHCRSP, which becomes a variant of the TSPTW (Dantzig & Ramser, 1959; Kumar & Panneerselvam, 2012). In this approach, we aim to minimize the weighted sum of costs associated with (1) travel times between locations, (2) overtime for each caregiver and (3) exceeding patients' time windows (maximize patient satisfaction). We propose formulating the HHCRSP as a MILP model and solving it with the commercial solver CPLEX version 20.1. As caregivers see, on average, seven patients per day (Irani et al., 2018), the instances to be solved are small, whereas CPLEX has shown great efficiency (IBM, 2022). The rescheduling approach goes as follows:

1. When a caregiver completes a visit, this patient is removed from their list.
2. Based on the current time, which is either earlier, later or the same as expected, we solve the MILP model with the remaining patients and time.
3. The patients are rescheduled for the rest of the day according to care constraints and minimization of total costs.

Once this problem is solved, the caregiver receives their new RS with the remaining patients on their list. Caregivers launch the rescheduling model after each patient's appointment to ensure that all delays and earliness throughout the day are considered. Once all visits are completed, the caregiver returns to the medical centre. Their return marks the end of their day.

Another thing to consider while scheduling and rescheduling patients are their availability. Hence, our second research question goes as follows:

How the length of patients' time windows affects the rerouting and rescheduling of caregivers?

The length of patients' time windows can impact the total costs of services. Short time windows could increase the risk of not respecting them, thus, increasing total costs. Larger time windows could reduce patients' satisfaction as they must be available for a longer period. If patients did not have time windows and were available all day, rescheduling would not be needed.

5. Mathematical Models

This section presents the mathematical formulation of the HHCRSP as a MILP model. Two formulations are provided: one for the first optimization (HHCRSP-1), which finds the initial schedule for each working caregiver, and one for the second optimization (HHCRSP-2), which reschedules the patients throughout the day based on the delays and earliness observed.

5.1 First Optimization: Initial Schedule

The first MILP model, HHCRSP-1, is based on Di Mascolo et al. (2021)'s mathematical formulation. The model finds the optimal route and schedule for caregivers to visit all their assigned patients daily. Giving a set of patients $i \in P = \{1, 2, \ldots, p\}$, where p is the total number of patients to be visited on a specific day, each caregiver in set $k \in N = \{1, 2, \ldots, k\}$, where k is the number of caregivers available, is assigned several patients. The distance between location l (medical centre or patient's home) and location m (medical centre or patients' home), where $l \neq m$, and the travel time to cover this distance are denoted by D_{lm} and T_{lm}, respectively. The unit for travel cost is KM $/minute. Each patient $i \in P$ has a visit duration V_i and their visit should ideally start in the time window $[PE_i, PL_i]$, where PE_i and PL_i are the earliest and latest starting times for patient i. Since there can be delays throughout the day, it is possible that patients can no longer be visited during their time window. For this reason, patients can be seen after the latest starting time of their time window, but at the cost of OW $/minute. Caregivers are available to work between the time interval $[NS_k, NE_k]$, where NS_k and NE_k are the start and the end of caregiver k's shift. They are allowed to work overtime at the cost of OV $/minute, to visit all patients on their list. Each caregiver has a lunch break of duration LB minutes, and it must be taken in the time interval $[BE_k, BL_k]$, where BE_k is the earliest start time and BL_k is the latest end time of the lunch break for caregiver k. Caregivers' workload, identified as w_k, is the sum of travel times and visit times. In order to balance the workload across caregivers, the maximum workload difference between caregivers has a cost of GAP $/minute.

We define the sets, indices, parameters, and decision variables as follows:

Table 1 Sets, indices, parameters and decision variables for the first optimization model

Sets	
P	Set of patients
N	Set of caregivers
A	Set of P ∪ N (necessary for caregivers and patients' locations)
Indices	
i, j	Patients, $i, j \in P$
k, h	Caregivers (medical centre), $k, h \in N$
l, m	Locations (patients' homes or medical centre), $l, m \in A$
Parameters	
$\boldsymbol{D_{lm}}$	Distance between location l and m
$\boldsymbol{T_{lm}}$	Travel time between location l and m
$\boldsymbol{PE_i}$	Earliest allowed service start time for patient i
$\boldsymbol{PL_i}$	Latest allowed service start time for patient i
$\boldsymbol{V_i}$	Visit duration for patient i
$\boldsymbol{NS_k}$	Shift start for caregiver k
$\boldsymbol{NE_k}$	Shift end for caregiver k
$\boldsymbol{BE_k}$	Earliest allowed time to start the lunch break
$\boldsymbol{BL_k}$	Latest allowed time to end the lunch break
$\boldsymbol{LB}$	Lunch break duration
$\boldsymbol{KM}$	Unit travel cost ($/min)
$\boldsymbol{OV}$	Cost of overtime ($/min)
$\boldsymbol{GAP}$	Cost of workload difference between caregivers ($/min)
$\boldsymbol{OW}$	Cost of seeing a patient after their time window ($/min)
$\boldsymbol{M}$	A large positive constant (big-M)
Decision variables	
$\boldsymbol{x_{lmk}}$	1 if caregiver k directly visits location m after location l, and 0 otherwise
$\boldsymbol{y_{ik}}$	1 if caregiver k takes a lunch break before visiting patient i, and 0 otherwise
$\boldsymbol{y'_{ik}}$	1 if caregiver k takes a lunch break after visiting patient i, and 0 otherwise
$\boldsymbol{s_{ik}}$	Service start time for patient i if they are visited by caregiver k
$\boldsymbol{b_k}$	Start of lunch break by caregiver k
$\boldsymbol{over_k}$	Overtime required from caregiver k
$\boldsymbol{w_k}$	Workload of caregiver k
$\boldsymbol{g}$	Difference between caregivers' workloads (auxiliary variable to model the maximum)
$\boldsymbol{ot_{ik}}$	Time required to see patient i outside their time window by caregiver k

Objective Function & Constraints

We consider an objective function that combines the total travel time of caregivers (term I), the total overtime of caregivers (term II), the maximal workload difference between caregivers (term III) and the total time exceeding patients' time windows (term IV).

$$Min\ F = \underbrace{KM \sum_{k \in N} \sum_{l \in A} \sum_{m \in A} T_{lm} * x_{lmk}}_{\mathrm{I}} + \underbrace{OV \sum_{k \in N} over_k}_{\mathrm{II}} + \underbrace{GAP * g}_{\mathrm{III}} + \underbrace{OW \sum_{k \in N} \sum_{i \in P} ot_{ik}}_{\mathrm{IV}} \quad (1)$$

The first model minimizes Objective Function (1). The following constraints restrict the objective function.

$$\sum_{k \in N} \sum_{\substack{l \in A \\ l \neq i}} x_{ilk} = 1 \qquad \forall i \in P \qquad (2)$$

Constraint (2) ensures that each patient is visited once by a caregiver.

$$\sum_{\substack{l \in A \\ l \neq i}} x_{lik} = \sum_{\substack{l \in A \\ l \neq i}} x_{ilk} \qquad \forall i \in P, k \in N \qquad (3)$$

Constraint (3) represents inflow/outflow conditions for caregivers visiting patients. It ensures that a caregiver who visits a patient leaves the patient’s house to see another patient or return to the medical centre.

$$\sum_{i \in P} x_{kik} = 1 \qquad \forall k \in N \qquad (4)$$

$$\sum_{i \in P} x_{ikk} = 1 \qquad \forall k \in N \qquad (5)$$

$$x_{hik} = 0, \qquad \forall i \in P, k \in N, h \in \{N : h \neq k\} \qquad (6)$$

Constraints (4) and (5) ensure that caregivers start and finish their day at the medical centre, i.e., their initial location. For example, if there are 15 patients and two caregivers, k would equal 16 and 17 to represent caregivers 1 and 2, respectively. k would represent their initial and final location at the same time as their identification for the patients’ assignation. Constraint (6) guarantees that a caregiver does not go to another caregiver’s house.

$$s_{ik} + V_i + T_{ij} - M(1 - x_{ijk}) \leq s_{jk} \qquad k \in N, \forall i \in P, \forall j \in \{P : j \neq i\} \qquad (7)$$

Constraint (7) determines the visit start time for patients visited by a specific caregiver. It is based on the visit duration, the travel time, and the visit’s start time of the previous patient. (See constraints (9) to determine the start time of the first patient.) Patient j's visit time will start when patient i's visit is completed, and the caregiver has completed the travel between location i and j.

$$PE_i \leq s_{ik} \leq PL_i + ot_{ik} \qquad \forall i \in P, k \in N \qquad (8)$$

Constraint (8) ensures that patients are visited during their time window, based on their earliest and latest start times. It also allows exceeding the patient's time window by increasing the value of the variable ot_{ik}. However, caregivers are not allowed to start an appointment earlier than the patient's earliest start.

$$NS_k - M(1 - x_{kik}) \leq s_{ik} - T_{ki} \qquad \forall i \in P, k \in N \qquad (9)$$

Constraint (9) guarantees that a caregiver cannot visit a patient until they have started their day and completed the travel to a patient's house.

$$NE_k + M(1 - x_{ikk}) + over_k \geq s_{ik} + V_i + T_{ik} \qquad \forall i \in P, k \in N \qquad (10)$$

Constraint (10) determines the amount of overtime (if required) per caregiver, based on the end of their shift and the time the last patient visited before returning to the medical centre.

$$\sum_{i \in P} T_{ki} * x_{kik} + \sum_{i \in P} \sum_{\substack{l \in A \\ l \neq i}} V_i * x_{ijk} + \sum_{i \in P} \sum_{\substack{j \in P \\ j \neq i}} T_{ij} * x_{ijk} + \sum_{i \in P} T_{ik} x_{ikk} \leq \mathrm{w}_k \qquad \forall k \in N \qquad (11)$$

$$w_k - w_h \leq g \qquad \forall k \in N, \forall h \in \{N : h \neq k\} \qquad (12)$$

Constraint (11) calculates each caregiver's workload, while Constraint (12) helps determine the maximal workload difference.

$$\sum_{i \in P} y_{ik} + \sum_{i \in P} y'_{ik} = \sum_{i \in P} x_{ikk} \qquad \forall k \in N \qquad (13)$$

$$y_{ik} + y'_{ik} \leq \sum_{l \in A} x_{ilk} \qquad \forall i \in P, k \in N \qquad (14)$$

$$b_k + LB * y_{ik} \leq s_{ik} + \mathrm{M}(1 - y_{ik}) \qquad \forall i \in P, k \in N \qquad (15)$$

$$s_{ik} + \left(V_i + t_{ij}\right) * (x_{ijk} + y_{jk} - 1) \leq b_k + \mathrm{M}(2 - x_{ijk} - y_{jk}) \qquad \forall i, j \in P, k \in N \qquad (16)$$

$$b_k + \left(LB + t_{ij}\right) * \left(x_{ijk} + y'_{ik} - 1\right) \leq s_{jk} + \mathrm{M}\left(2 - x_{ijk} - y'_{ik}\right) \qquad \forall i, j \in P, k \in N \qquad (17)$$

$$s_{ik} + V_i * y'_{ik} \leq b_k + \mathrm{M}(1 - y'_{ik}) \qquad \forall i, j \in P, k \in N \qquad (18)$$

$$BE_k \leq b_k \leq BL_k \qquad \forall k \in N \qquad (19)$$

Constraints (13) and (14) ensure that each caregiver takes a break before or after visiting a patient. Constraints (15) to (18) determine the start time of the lunch break, depending on whether the lunch will be taken before or after visiting a patient. Constraint (19) ensures that caregivers take their lunch break during the predetermined time interval.

5.2 Second Optimization: Rescheduling patients

We use the same mathematical model for the second optimization. Still, we adapt it to the new problem where we consider only one caregiver at the time with their list of patients, which can not be changed (HHCRSP-2). This last assumption is made because, as already mentioned, caregivers only take the necessary equipment and medications to see the patients on their list. Hence, they can only visit other patients on their list. The modifications to the model go as follow:

- First, we do not need to consider the caregiver's workload in the second optimization as the balancing has been considered in the first one. Hence, we remove Constraints (11) and (12) and the parameter III from the initial mathematical model.
- Second, we remove Constraint (6) as it is now impossible for caregivers to go to another caregiver's place.
- Third, we create new sets and indices to always know the initial and final position of the caregiver (see Table 2). The initial position is the location of the completed patient visit, and the final position is the medical centre.
- Finally, we create two versions of the rescheduling model: one where the caregiver has not taken their lunch and one where the caregiver has taken their lunch.

Below, we present a framework where the rescheduling model would be embedded for daily use. The caregivers will have to use an app to execute the rescheduling model and be aware of their new optimal RS. The steps below describe how the app would work and when the rescheduling model is launched:

1. The caregiver starts their day by seeing the first patient on their list.
2. Once the visit is completed, the caregiver enters their caregiver's ID number in the app.
3. The caregiver enters the completed patient's ID number.

4. This patient is removed from the caregiver's list of patients.
5. The start of the caregiver's shift (NS_k) is changed to the current time: when the patient is entered as "completed."
6. The caregiver mentions if they have taken their lunch break or not.
7. The rescheduling model (see below) is launched.
8. The caregiver receives an updated route and schedule.
9. The caregiver moves on to the next patient on the new schedule.
10. Steps 2 to 9 are repeated until there is only one patient on the caregiver's list.
11. Once they finish all the visits, they return to the medical centre.

Step 5 is where we consider whether the caregiver is running ahead or behind their current schedule. If the caregiver were delayed due to traffic jams on the road, it would be considered at the end of the visit. The visit would finish later than expected. Therefore, the subsequent patients will be rescheduled, considering the delay. If the visit were shorter than expected, it would also be considered since we are launching the rescheduling model at the current time, when the patient is entered as "completed" on the app.

We define the added and modified sets and indices as follows (parameters and decision variables are the same as in Table 1):

Table 2 Added and modified sets and indices for the second optimization model

Sets	
P	Set of patients
N	Set of caregivers (medical centre)
A	Set of P ∪ N (necessary for the medical centre and patients' locations)
D	Set of caregivers (caregivers' current location – previous patient location)
C	Set of P ∪ N ∪ D (necessary for all locations)
Indices	
i, j	Patients, $i, j \in P$
k	Caregivers (medical centre), $k \in N$
r	Caregivers (current position), $r \in D$
l, m	Locations (patients, caregivers' current location and medical centre), $l, m \in C$

Two mathematical formulations are described below, one with the lunch break's constraints and one without them. First, we present the objective function and constraints for the case where the caregivers have not taken their lunch yet.

Objective Function & Constraints

$$Min\ F' = KM \sum_{k\in N} \sum_{l\in C} \sum_{m\in C} T_{lm} * x_{lmk} + OV \sum_{k\in N} over_k + OW \sum_{k\in N} \sum_{i\in P} ot_{ik} \qquad (20)$$

Objective function (20) aims to minimize the total costs associated with travel time between locations, overtime and seeing patients outside their time window. The following constraints restrict the objective function.

$$\sum_{k\in N} \sum_{\substack{l\in A \\ l\neq i}} x_{ilk} = 1 \qquad \forall i \in P \qquad (21)$$

$$\sum_{\substack{m\in C \\ m\neq k}} x_{mik} = \sum_{\substack{l\in A \\ l\neq i}} x_{ilk} \qquad \forall i \in P, k \in N \qquad (22)$$

$$\sum_{i\in P} x_{rik} = 1 \qquad \forall k \in N, \forall r \in D \qquad (23)$$

$$\sum_{i\in P} x_{ikk} = 1 \qquad \forall k \in N \qquad (24)$$

Constraint (21), like Constraint (2), ensures that all patients are visited once. Constraint (22) represents inflow/outflow conditions for the caregiver visiting patients. It ensures that the caregiver who sees a patient leaves the patient's house to visit another patient or return to the medical centre. Constraint (23) ensures that the caregiver will start their new route from the completed patient's location. Once the rescheduling model is launched, it is necessary to consider the caregiver's current position as the beginning of the updated route. Constraint (24) ensures that the caregiver will finish at the medical centre.

$$s_{ik} + V_i + T_{ij} - M(1 - x_{ijk}) \leq s_{jk} \qquad k \in N, \forall i \in P, \forall \in \{P: j \neq i\} \qquad (25)$$

$$PE_i \leq s_{ik} \leq PL_i + ot_{ik} \qquad \forall i \in P, k \in N \qquad (26)$$

As Constraint (7) and (8), Constraint (25) determines the visit start time for patients visited by the caregiver, and Constraint (26) ensures that the visits begin in the specified time interval. It is possible to exceed the patients' time windows to ensure that all patients are visited during the day.

$$NS_k - M(1 - x_{rik}) \leq s_{ik} - T_{ri} \qquad \forall i \in P, k \in N, r \in D \quad (27)$$

As the caregiver completes patients' visits throughout the day, the value NS_k is updated to the end of an appointment. Constraint (27) ensures that the following patient's visit can not start before the caregiver's new shift starts, and the travel time to go to this patient's house is considered.

$$NE_k + M(1 - x_{ikk}) + \ over_k \geq s_{ik} + V_i + T_{ik} \qquad \forall i \in P, k \in N \qquad (28)$$

Constraint (28), like Constraint (10), determines the amount of overtime required.

$$\sum_{i \in P} y_{ik} + \ \sum_{i \in P} y'_{ik} = \sum_{i \in P} x_{ikk} \qquad \forall k \in N \qquad (29)$$

$$y_{ik} + y'_{ik} \leq \sum_{l \in A} x_{ilk} \qquad \forall i \in P, k \in N \qquad (30)$$

$$b_k + LB * y_{ik} \leq s_{ik} + \mathrm{M}(1 - y_{ik}) \qquad \forall i \in P, k \in N \qquad (31)$$

$$s_{ik} + \left(V_i + t_{ij}\right) * (x_{ijk} + y_{jk} - 1) \leq b_k + \mathrm{M}(2 - x_{ijk} - y_{jk}) \qquad \forall i, j \in P, k \in N \qquad (32)$$

$$b_k + \left(LB + t_{rj}\right) * (x_{rik} + y_{ik} - 1) \leq s_{ik} + \mathrm{M}(2 - x_{rik} - y_{ik}) \qquad \forall i \in P, k \in N, r \in D \qquad (33)$$

$$b_k + \left(LB + t_{ij}\right) * \left(x_{ijk} + y'_{ik} - 1\right) \leq s_{jk} + \mathrm{M}\left(2 - x_{ijk} - y'_{ik}\right) \qquad \forall i, j \in P, k \in N \qquad (34)$$

$$s_{ik} + V_i * y'_{ik} \leq b_k + \mathrm{M}(1 - y'_{ik}) \qquad \forall i, j \in P, k \in N \qquad (35)$$

$$BE_k \leq b_k \leq BL_k \qquad \forall k \in N \qquad (36)$$

Like Constraints (13) and (14), Constraints (29) and (30) determine if the caregiver will take their lunch right before visiting a patient or right after. Constraints (31) to (35) determine the start time of the lunch break, depending on whether the caregiver takes their lunch right after or right before visiting a patient. As Constraint (19), Constraint (36) ensures that the lunch break happens in the specified time interval.

Finally, once the caregivers have taken their lunch, the mathematical model stays the same, but we remove Constraints (29) to (36). The model becomes easier to solve as fewer constraints are to be considered.

6. Results

The data generation process, the creation of instances and the results are presented in the following section.

6.1 Data Generation

This section describes the problem instances generated to test the proposed mathematical approach. Section 6.1.1 presents the data generated for caregivers, and Section 6.1.2 presents the data generated for patients. Finally, the values used for the other parameters are presented in Section 6.1.3. Table 3 shows a summary of the values generated.

6.1.1 Data Generation for Caregivers

- Caregivers are working ten hours per day (600 minutes). Days start at minute 0 (i.e., 8 am) and end at minute 600 (i.e., 6 pm).
- Caregivers have a one-hour (60 minutes) break for lunch. The break time cannot start before minute 180 (i.e., 11 am) and must finish before minute 360 (i.e., 2 pm).
- Caregivers start their day at the medical centre with the coordinate (0, 0) and end it at the medical centre. Once at the medical centre, they take the equipment and medication to treat the patients on their list.
- Caregivers are allowed overtime to see all the patients on their list. Every minute of overtime is charged at a higher cost than their regular hours.

6.1.2 Data Generation for Patients

- Patients' visit durations differ, going from 15 to 60 minutes. A blood collection visit lasts 15 to 30 minutes (LifeLabs, 2022), while a physiotherapy appointment may last up to 60 minutes (PhysioCare At Home, 2022). The duration is defined randomly following a uniform distribution. A uniform distribution is chosen because all patients needing care on a specific day might have different visit durations based on the type of treatment they need. Hence, this distribution helps randomly define the planned visit duration for patients.
- Patients' locations are also determined randomly, following a uniform distribution. Their coordinates go from [-30, 30] on the X axe and [-30, 30] on the Y axe (see Appendix 1 for further details).
- Euclidean distances are considered. The coordinates are based on the travel time to cover the Ottawa region (See Appendix 1). We assume that one distance unit equals one minute of travel time. Based on this assumption, it takes 84 minutes to cover the longest distance from position (-30, -30) to position (30, 30).
- A patient's time window starts between minute 0 to minute 330. This starting time is defined randomly, following a uniform distribution. The caregiver can arrive anytime after the earliest possible start of the patient's time window to start the visit. The earliest possible start is minute 0 (i.e., 8 am), and the latest possible start is minute 330 (i.e., 1:30 pm).

- A patient's time window has a specific duration. Different lengths are being compared in this study. We are testing time windows of 180 minutes (three hours), 240 minutes (four hours), and 300 minutes (five hours). Smaller time windows than 180 minutes are not considered because it would not allow enough flexibility to reschedule patients since the maximum possible travel time (84 minutes) added to the longest appointment (60 minutes) is 144 minutes. Also, we do not consider larger time windows because 300 minutes represent a half-day in this study; hence we do not want patients waiting longer than half a day.
- To allow flexibility in the creation of schedules, and in case of delays throughout the day, caregivers can exceed patients' time windows. Every minute exceeding the patients' time windows has a cost.

6.1.3 Other Parameters

In the first optimization, we aim to balance the cost of travelling between locations, the cost of overtime from caregivers, the cost of the maximum workload difference between caregivers, and the cost of exceeding patients' time windows. The unit cost for each term is expressed in ($/min); hence we can use a summation in the objective function.

- We assume that travel, visits, and idle time would cost the same as caregivers working through their shift. We consider that travel time (KM) would cost 1$/minute.
- We assume overtime (OV) costs 1.5$/minutes, which is 1.5 times higher than regular time and respects Ontario rules on overtime (Government of Ontario, 2022).
- The workload equals the sum of the total travel time and the total visit time for each caregiver. According to Yang et al. (2021), minimizing travel cost and workload balance are objectives that can be achieved simultaneously. Decerle et al. (2018-B) stated that it is easier to have a trade-off between balancing the workload and other parameters from the objective function if the workload and the other objective have a close definition. In our case, the workload and another parameter from the objective function consider travel time. Therefore, we assume that the time difference between caregivers' workload (GAP) is considered the same ratio as regular travel time cost, which is 1$/minute.
- Finally, to respect as much as possible patients' time windows, and due to the importance of this constraint, we define the penalty associated with exceeding the patients' time

windows (OW) as ten times higher than travel time. Hence, this means that OW is set at 10$/minute.

In the second optimization, we aim to minimize the cost of travelling between locations, the cost of overtime from caregivers and the cost of seeing patients outside their time windows. KM, OV and OT remain at the same value in the second optimization phase in order to be able to make a fair comparison of the results.

6.1.4 Simulation of Delays

According to the literature (Andreyeva et al., 2018), the standard deviation of the duration of a visit is approximately 20 minutes. Since we have visits lasting 15 minutes, we can not use a mean of zero minutes to simulate the delays. Hence, we assume the delays have a value of [-10, 30] minutes, knowing appointments may last longer than planned more often than finishing earlier (Andreyeva et al., 2018). Appointments can end up to 10 minutes earlier than expected (the minimum appointment length possible is five minutes) and 30 minutes later than expected (the maximum appointment length possible is 90 minutes). We simulate delays randomly following a uniform distribution to ensure equal probability for all outcomes. This distribution provides random delays or earliness, representing the reality as we do not know the future time uncertainties.

Table 3 presents the values defined for the data generation of each parameter.

Table 3 Data generation values

Parameters	Values
Caregivers start	0 minute
Caregivers end	600 minutes
Caregivers break time	[180, 360] minutes
Break length	60 minutes
Caregivers position (medical centre)	(0, 0)
Visit duration	[15, 60] minutes
Patients' location – X Position	[-30, 30]
Patients' location – Y Position	[-30, 30]
Patients' earliest start	[0, 330] minutes
Patients' time windows	180, 240, 300 minutes
KM – Cost for travel time	1$/min
OV – Cost for overtime	1.5$/min
GAP – Cost for the time difference between caregivers' workload	1$/min
OW – Cost for exceeding patients' time windows	10$/min
Delays	[-10, 30] minutes

6.2 Instances

In order to evaluate the performance of the suggested approach, we created different instances to simulate different scenarios (see Table 4). Each instance was generated by the method described in Section 6.1. Each set has 15 different instances. Sets A, B, and C all have two caregivers and 15 patients, with patients' time windows of 180, 240 and 300 minutes, respectively. Sets E, D, and F all have two caregivers and 18 patients, with patients' time windows of 180, 240 and 300 minutes, respectively. Finally, sets G, H, and I all have three caregivers and 20 patients, with patients' time windows of 180, 240 and 300 minutes, respectively.

Table 4 Instances

Instance set	Number of instances	Number of caregivers	Number of patients	Length of time windows (minutes)
A	15	2	15	180
B	15	2	15	240
C	15	2	15	300
D	15	2	18	180
E	15	2	18	240
F	15	2	18	300
G	15	3	20	180
H	15	3	20	240
I	15	3	20	300

A total of 135 instances were created. This equals the number of times the first optimization model was solved. The second optimization model, i.e., the rescheduling, was applied to each caregiver individually, which equals 315 rescheduling tests. Table 5 presents the total number of tests completed.

Table 5 Total number of tests

Instance sets	Number of sets
Total number of instances	135
Total number of rescheduling tests	315

6.3 Test Results

To understand the importance of the results obtained using the rescheduling approach, we compared the results obtained to the initial schedule. The comparison is called the reverse approach. In order to have a fair comparison of both approaches, we applied the delays from the rescheduling optimization to the appointments in the initial schedule. For example, suppose appointment Y finishes 15 minutes later than expected. We apply these 15 minutes delays to appointment Y in the initial schedule, no matter the order of the visits. This way, each appointment has the same duration in both rescheduling and reverse approaches. We then compared the results based on the second optimization's objective function, which is in terms of travel time, overtime, and violation of time windows.

Both MILP models were coded in PyCharm 2020.3.5, for which the interpreter is Python 3.7, and ran on an Intel(R) Core i7-10510U CPU with 8 GB of DDR3 RAM with IBM ILOG CPLEX 20.1 as the solver. The computation time for the first optimization model was limited to 2400 seconds. The second optimization model was solved instantly.

Section 6.3.1 presents the complete analysis for one instance from set C, and Section 6.3.2 presents the analysis of all tests.

6.3.1 Example of Analysis

Below is an example of how the models work together. We present an example with two caregivers and 15 patients with five-hour time windows. Table 6 shows the data generated for the patients. For each patient, the earliest start time, the latest start time, the planned visit duration, and the location are provided. Table 7 presents the data generated for the caregivers. For each caregiver, a start shift time, an end shift time, an earliest lunch break time and a latest lunch break time are provided.

Table 6 Data generated for 15 patients with five-hour time windows

Patient's number	Earliest start (PE_i) (min)	Latest start (PL_i) (min)	Planned visit duration (V_i) (min)	X Position	Y Position
1	237	537	36	29	1
2	154	454	46	-14	-29
3	41	341	30	29	8
4	28	328	55	14	-6
5	137	437	47	-2	-30
6	293	593	31	-24	-2
7	19	319	47	-18	23
8	193	493	53	25	-5
9	42	342	21	18	-1
10	319	619	19	22	12
11	87	387	31	-20	-10

Patient's number	Earliest start (PE_i) (min)	Latest start (PL_i) (min)	Planned visit duration (V_i) (min)	X Position	Y Position
12	35	335	28	18	12
13	19	319	55	-24	15
14	191	491	30	23	27
15	126	426	53	14	15

Table 7 Data generated for two caregivers

Caregiver	Start of shift (NS_k) (min)	End of shift (NE_k) (min)	Earliest lunch (BE_k) (min)	Latest lunch (BL_k) (min)	X Position	Y Position
1	0	600	180	360	0	0
2	0	600	180	360	0	0

Once the data for each patient and caregiver are generated, the first optimization model provides the routing for each caregiver to visit patients on their list starting and finishing at the medical centre (Figure 1) and an optimal initial schedule (Table 8).

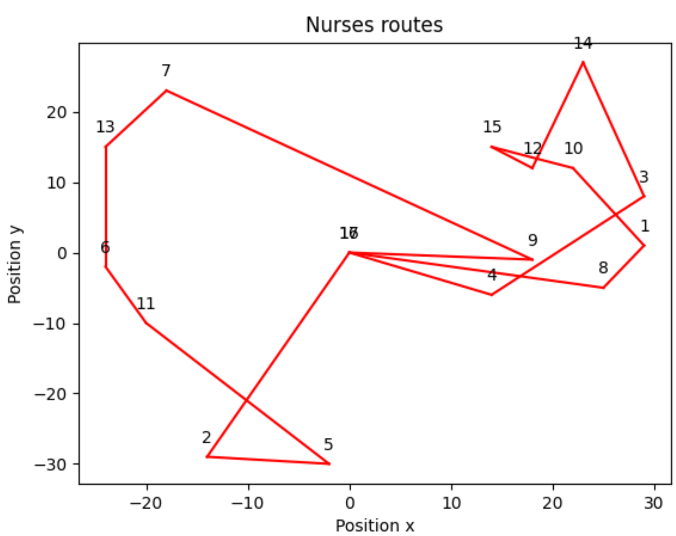

Figure 1 Caregivers' routing based on patients' location

Table 8 Initial schedule

Caregiver k	**Patient i**	**l (Start location)**	**m (End location)**	T_{lm}	s_{ik}	V_i	**End Visit**	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	**xPos**	**yPos**	ot_{ik}
16	1	9	7	43	42	21	63	42	342					18	-1	-300
16	2	7	13	10	106	47	153	19	319					-18	23	-213
16	3	13	6	17	163	55	218	19	319					-24	15	-156
16	4	6	11	9	295	31	326	293	593					-24	-2	-298
16	5	11	5	27	335	31	366	87	387					-20	-10	-52
16	6	5	2	12	395	47	442	137	437					-2	-30	-42
16	7	2	16	32	454	46	500	154	454					-14	-29	0
17	1	4	3	21	28	55	83	28	328					14	-6	-300
17	2	3	14	20	104	30	134	41	341					29	8	-237
17	3	14	12	16	191	30	221	191	491					23	27	-300
17	4	12	15	5	297	28	325	35	335					18	12	-38
17	5	15	10	9	330	53	383	126	426					14	15	-96
17	6	10	1	13	392	19	411	319	619					22	12	-227
17	7	1	8	7	424	36	460	237	537					29	1	-113
17	8	8	17	25	493	53	546	193	493					25	-5	0
16		16	9	18						235	180	360	0	0	0	
17		17	4	15						237	180	360	0	0	0	

Each caregiver receives a list of patients to visit throughout the day. The start location l and end location m present the routing of each caregiver based on the patient's number from the generated data. In this specific scenario, locations 16 and 17 represent the medical centre and the identification of caregiver 16 (i.e., caregiver 1) and caregiver 17 (i.e., caregiver 2). $\boldsymbol{T_{lm}}$ calculates the travel time to go from location l to location m. Each patient is assigned a start time ($\boldsymbol{s_{ik}}$). For example, the first patient on caregiver 1's list starts their visit at minute 42 and ends at minute 63. Then, it takes 43 minutes to go from the first patient to the second one. The visit start time of the second patient cannot be earlier than minute 106. The initial schedule also calculates the time exceeding patients' time windows ($\boldsymbol{ot_{ik}}$). Each positive value means the caregiver has exceeded the patient's latest start ($\boldsymbol{PL_i}$) when the visit started. Finally, the initial schedule also indicates when the caregivers will have to take their lunch ($\boldsymbol{b_k}$) and their overtime required ($\boldsymbol{over_k}$).

The rescheduling model, the second optimization, is solved after each completed appointment to reschedule the subsequent patients to ensure the delays and earliness are captured. Appendix 2 shows how visits are rescheduled based on the delays throughout the day. The initial and final routings for each caregiver are presented in Table 9. Figures 2 and 3 show the initial route and schedule, the initial routing with delays, i.e., the routing representing the reverse approach and the rescheduled routing, i.e., the routing representing the rescheduling approach, for caregivers 1 and 2, respectively.

Table 9 Initial and final routing for both caregivers

Caregivers	**Caregiver 1**	**Caregiver 2**
Initial routing	16 → 9 → 7 → 13 → 6 → 11 → 5 → 2 → 16	17 → 4 → 3 → 14 → 12 → 15 → 10 → 1 → 8 → 17
After rescheduling	16 → 9 → 7 → 13 →**11 → 5 → 2 → 6** → 16	17 → 4 → **12 → 3 → 14** → 15 → 10 → **8 → 1** → 17

In caregiver 16's final routing, patients 11, 5, 2 and 6 are rescheduled. In caregiver 17's final routing, patients 12, 3, 14, 8 and 1 are rescheduled.

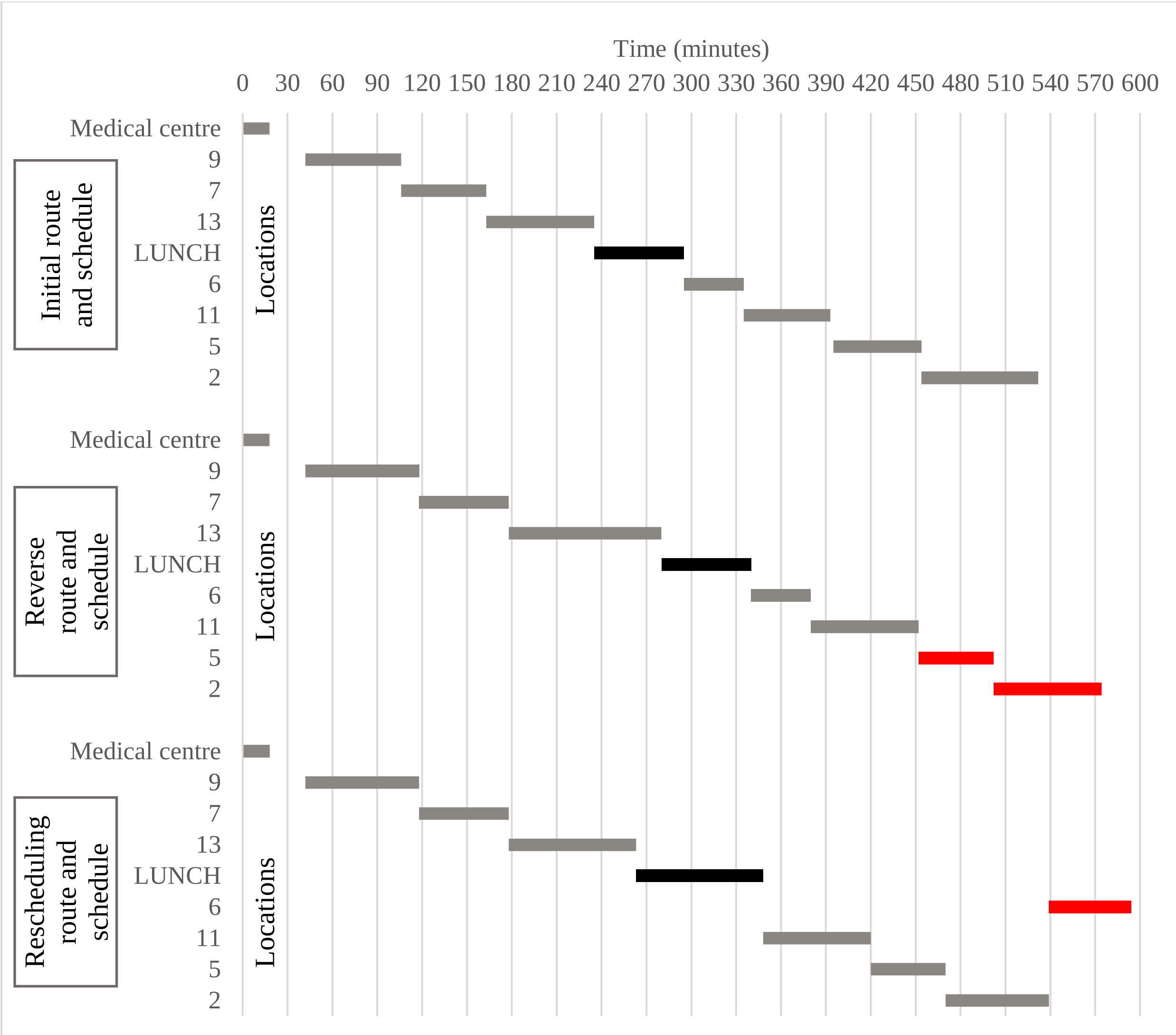

Figure 2 Initial routing with delays and rescheduled routing for caregiver 1

In Figure 2, when delays were observed throughout the day, the rescheduling approach proposed rescheduling patient 6 at the end of the day instead of following the initial route. In the initial routing with delays (i.e., the reverse approach), the caregiver arrived 15 minutes later than the latest start time at patient 5's home and 48 minutes later at patient 2's home. In the rescheduled routing, the caregiver only arrived 16 minutes later than the latest start time at patient 2's home. Even with patient 6 being rescheduled at the end of the day, the total costs were lower since the time windows were still respected. Also, patient 6 did not realize their appointment was completed later than expected as the caregiver still respects their time windows. The total travel time in the initial routing was 168 minutes, while in the rescheduled routing, it was 188 minutes. No overtime was observed in both routings.

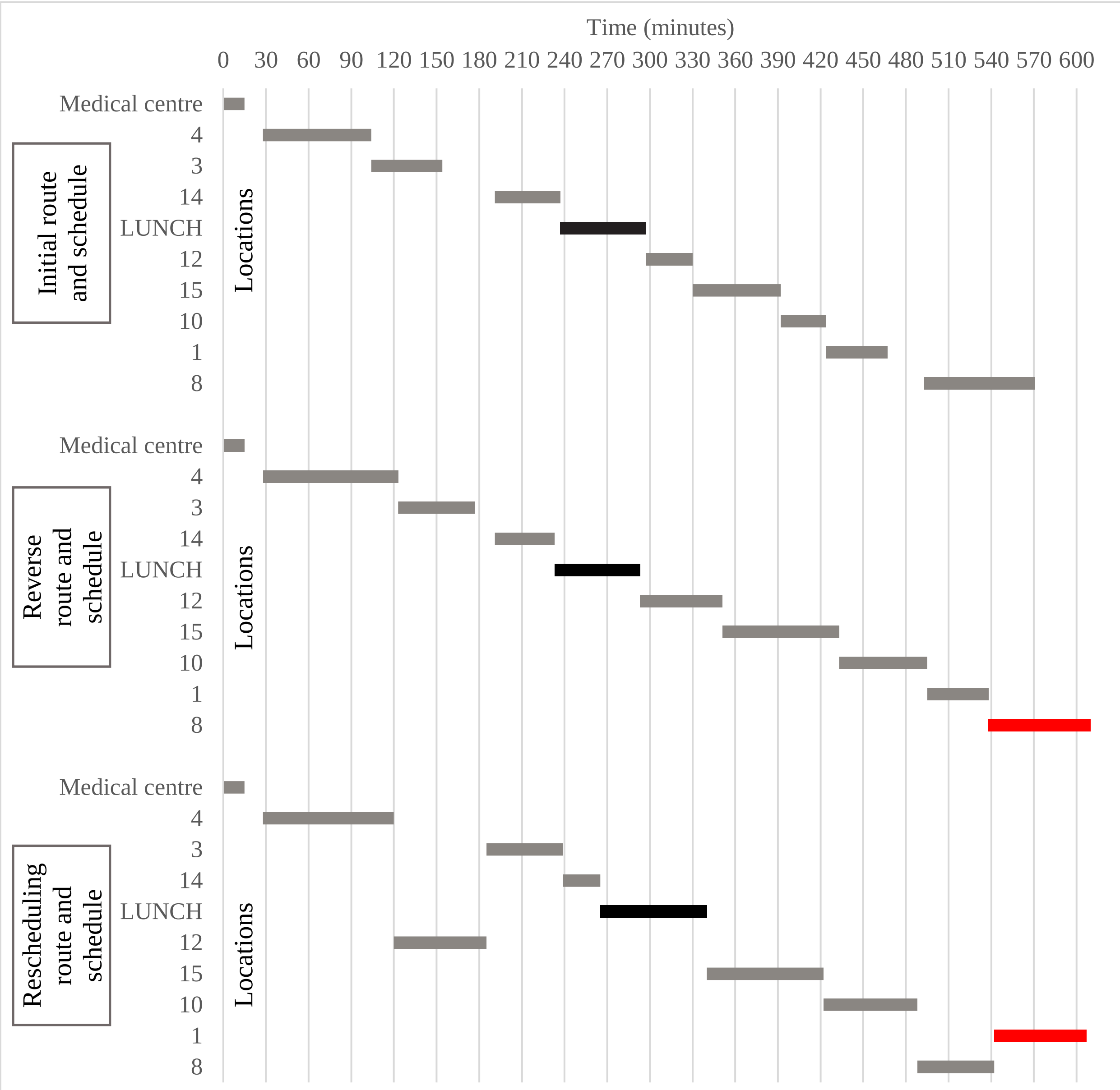

Figure 3 Initial routing with delays and rescheduled routing for caregiver 2

In Figure 3, we observed patients 12, 3, 14, 8 and 1 being rescheduled throughout the day. In the initial routing with delays (i.e., the reverse approach), the caregiver arrived 45 minutes later than the latest start time at patient 8's home. In the rescheduled routing, the caregiver only arrived 5 minutes later than the latest start time at patient 1's home. The total travel time in the initial routing was 131 minutes, while in the rescheduled routing, it was 142 minutes. Overtime of 7 minutes was observed in the rescheduled routing, while in the reverse one, we observed overtime of 10 minutes. Due to the delays observed throughout the day, the total costs with the rescheduling approach were lower than with the initial route.

The results from the reverse and reschedule approaches are presented below in Figure 4. We compared them based on each objective function term and the total costs.

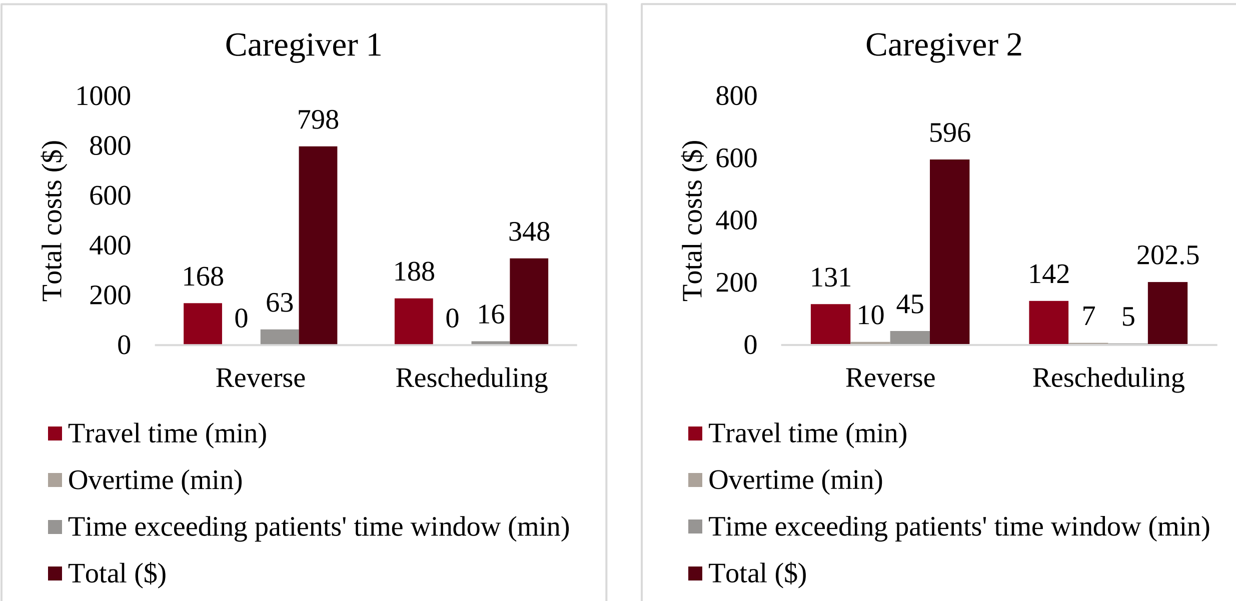

Figure 4 Comparison of the rescheduling and reverse approach for both caregivers

Based on this example, for both caregivers, the travel time was higher with the rescheduling approach, meaning they had to drive for a longer time in order to minimize total costs. Caregiver 2's overtime was higher with the reverse approach than with the rescheduling approach. Both caregivers time exceeding patients' time windows were smaller with the rescheduling approach, which was the most expensive cost in the objective function. Overall, the rescheduling approach saved 743.5$ on that day, compared to having done no rescheduling. This would have represented a 61% decrease in the total costs if the rescheduling approach had been used that day. Table 10 presents the total costs of that day per caregiver and the percentage decrease in total costs when using the rescheduling approach for this example. Equation (37) gives the calculation to determine the % of the decrease in total costs when applying the rescheduling approach.

$$Decrease\ (\%) = \left(\frac{Rescheduling\ approach\ costs - Reverse\ approach\ costs}{Reverse\ approach\ costs}\right) * -100 \qquad (37)$$

Table 10 Comparison of the rescheduling approach vs. reverse approach per caregiver

	Objective function (Reverse approach) ($)	Objective function (Rescheduling approach) ($)	Difference ($)	Decrease in total cost with rescheduling approach (%)
TOTAL COSTS	1394	550.5	843.5	61%
Caregiver 1	798	348	450	56%
Caregiver 2	596	202.5	393.5	66%

6.3.2 Analysis of Results

This section presents and analyses the results from all tests. We compared the total costs of activities per day per caregiver for both approaches: rescheduling and reverse. Table 11 indicates the number of tests analyzed by the number of patients visited in a day and the length of the time windows. Depending on the instance set, caregivers did not see the same number of patients daily.

Table 11 Number of tests by number of patients visited and length of the time windows

Time windows / Number of patients visited	3 hours	4 hours	5 hours	Total
5	*1*	*2*	*1*	*4*
6	20	16	15	51
7	35	39	42	116
8	24	25	23	72
9	17	15	18	50
10	8	7	6	21
11	*0*	*1*	*0*	*1*
Grand Total	**105**	**105**	**105**	**315**

Overall, 315 tests were performed. One hundred sixteen tests (36%) were performed with a caregiver visiting seven patients per day. We removed tests with five and 11 patients visited per day from the future analyses as there were too few tests with these numbers of patients; therefore, we could not conclude from the results. Hence, we analyzed 310 rescheduling tests, 104 tests with three-hour time windows, 102 tests with four-hour time windows and 104 tests with five-hour time windows.

Once the tests were completed, we calculated the total costs of the objective function when using the rescheduling approach and the reverse approach. Figure 5 presents the disparity of the total costs, and Table 12 shows the independent sample t-test results comparing both methods.

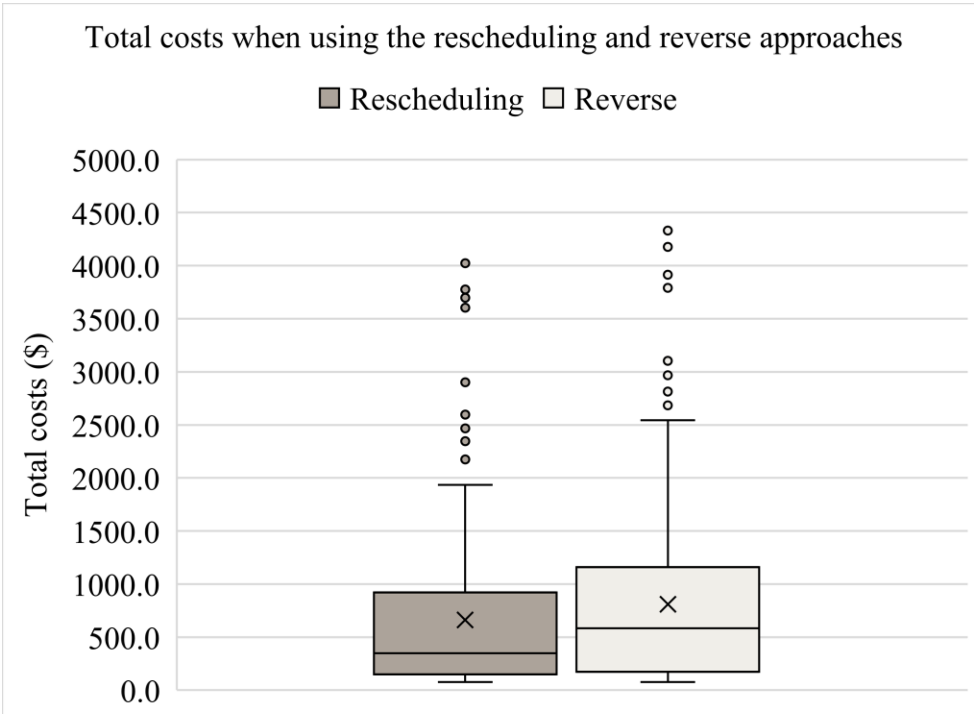

Figure 5 Disparity of results with the rescheduling approach and reverse approach

Table 12 Independent sample t-test results comparing the rescheduling and reverse approaches

Groups	**Rescheduling**	**Reverse**
Number of tests	310	310
Mean	662$	809$
Median	348$	584.5$
Standard deviation	720$	806$
Standard Error Mean	40.89	45.79
Minimum	77$	77$
Q1	149$	173$
Q3	1158.5$	921$
Maximum	4022$	4331.5$
t	2.3962	
df	618	
***p*-value**	0.0169	

The average costs calculated with the rescheduling approach were lower than with the reverse approach (662$/test with a median value of 348$ vs. 809$/test with a median value of 584.5$, respectively). Both methods had the same minimal value (77$/day), but the rescheduling approach presented a lower Q1 value than the reverse one (149$ vs. 173$). The reverse approach presented a higher Q3 value than the rescheduling approach (1158.5$ vs. 921$). Finally, according to the t-test results (2.3962 > 2), there exists a large difference between the two approaches. Also, the p-value indicates that the difference is considered to be statistically significant (p-value < 0.05). Hence, we can assume that the rescheduling approach affected the total costs. Overall, the costs were lower with the rescheduling approach than with the reverse approach, but both methods showed a great disparity.

Table 13 compares the results from the rescheduling and reverse approaches. It presents the number of instances with a decrease, an increase and no impact on total costs when using the rescheduling approach. Appendix 3 gives further details on the results obtained for each instance set.

Table 13 Impact of using the rescheduling vs. reverse approaches on total costs

		Decrease	**Increase**	**No change**	**Total**
	Number of tests	150	47	113	310
	% of total	48.39%	15.16%	36.45%	100%
Rescheduling	Average objective function ($)	802	795	421	662
	Standard deviation ($)	856	656	432	720
	Variance	732163	430951	186781	518362
Reverse	Average objective function ($)	1151	652	421	809
	Standard deviation ($)	928	589	432	806
	Variance	860846	347447	186781	650004
Difference between rescheduling & reverse	Average objective function ($)	349	-143	0	147
	Standard deviation ($)	320	161	0	306
	Variance	102719	25946	0	93864

The rescheduling approach reduced the total cost in 48.39% of the cases by an average of 349$ per test when a decrease was observed. In comparison, the reverse approach reduced total costs in 15.16% of the cases by 143$ per test when a reduction was observed. In 36.45% of the cases, applying either technique did not affect the total cost. Overall, using the rescheduling approach reduced or did not impact total costs in 85.22% of the cases. On average, costs were decreased by 147$ per instance, with a standard deviation of 306$, representing a total cost decrease of

14% (See Figure 6). With the rescheduling approach, finding a local optimal solution that considers those delays is possible since we are no longer on the optimal path due to delays. Hence, this approach positively impacts total costs to ensure delays or earliness are captured.

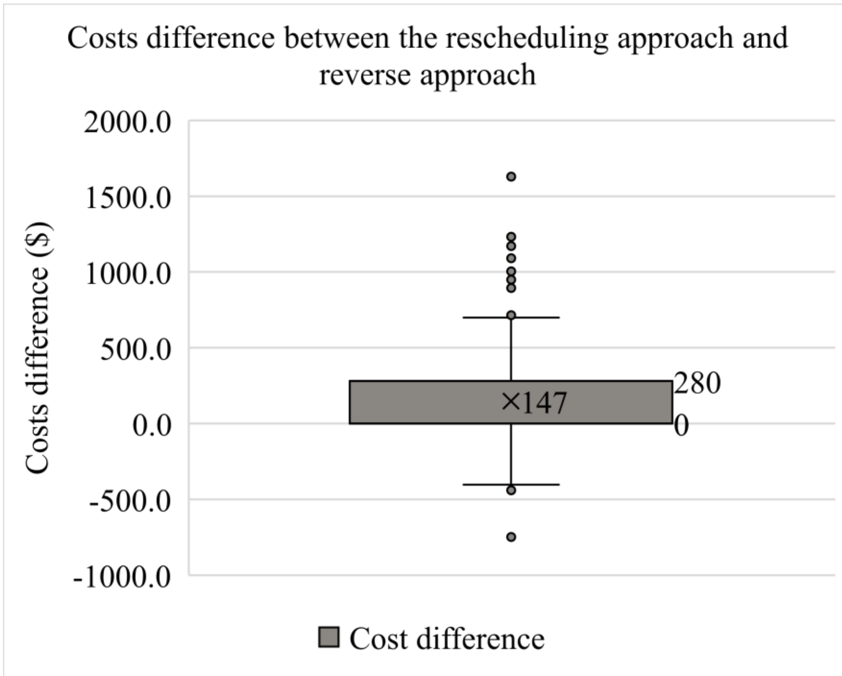

Figure 6 Disparity of the costs difference observed with the rescheduling approach

Most of the tests positively impacted the total cost when applying the rescheduling approach (a positive value represented a decrease in total cost when using the rescheduling approach, while a negative one represented an increase). 50% of the results presented saving between 0$ and 280$ when using the rescheduling approach compared to the reverse approach, with an average of 147$.

Figure 7 shows the number of instances decreasing and increasing the total costs when using the rescheduling approach.

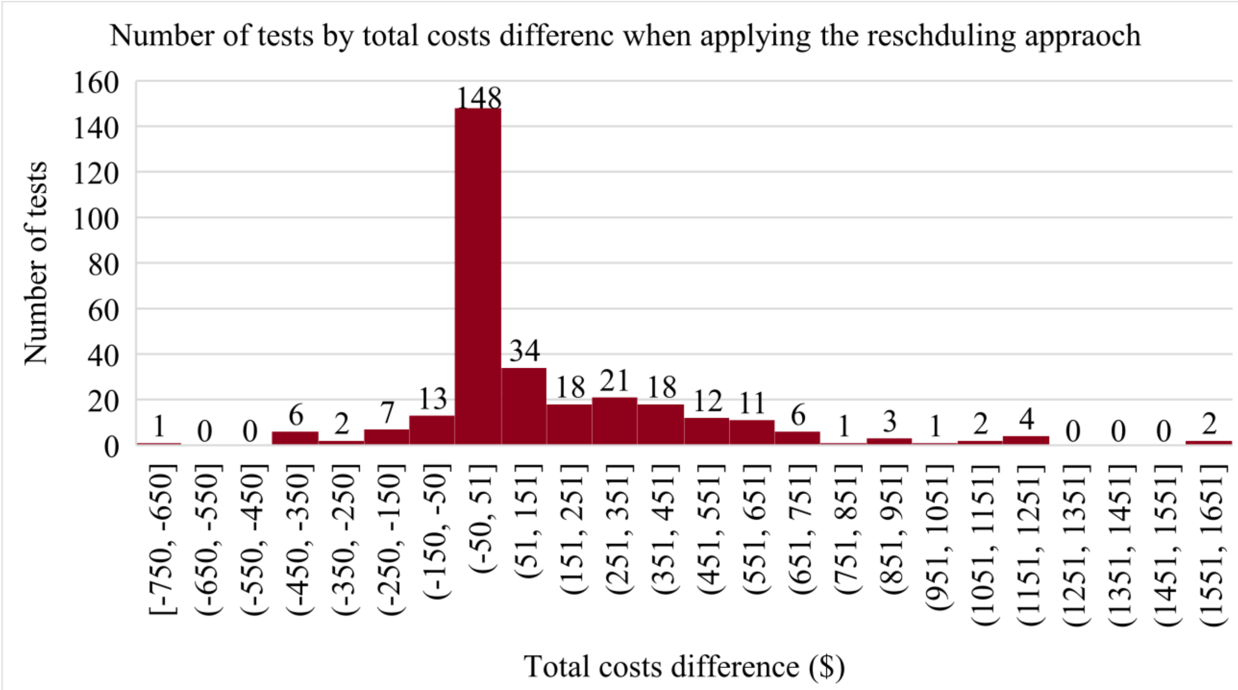

Figure 7 Number of tests by total costs difference when applying the rescheduling approach

From the 310 tests, 148 (48%) had a total cost difference of (-50$, 51$] when using the rescheduling approach. This result included 113 instances without impact on total costs. Ninety-one instances (29%) had a total cost decrease of (51$, 451$] compared to 28 instances (9%), increasing the total costs from [51$, 450$].

The second research question involved the impact of the length of the time windows on the results. Figure 8 shows the disparity of the total costs with the reverse and rescheduling approaches by the length of the time windows, and Table 14 presents the analysis of the impact of the length of the time windows on the total costs.

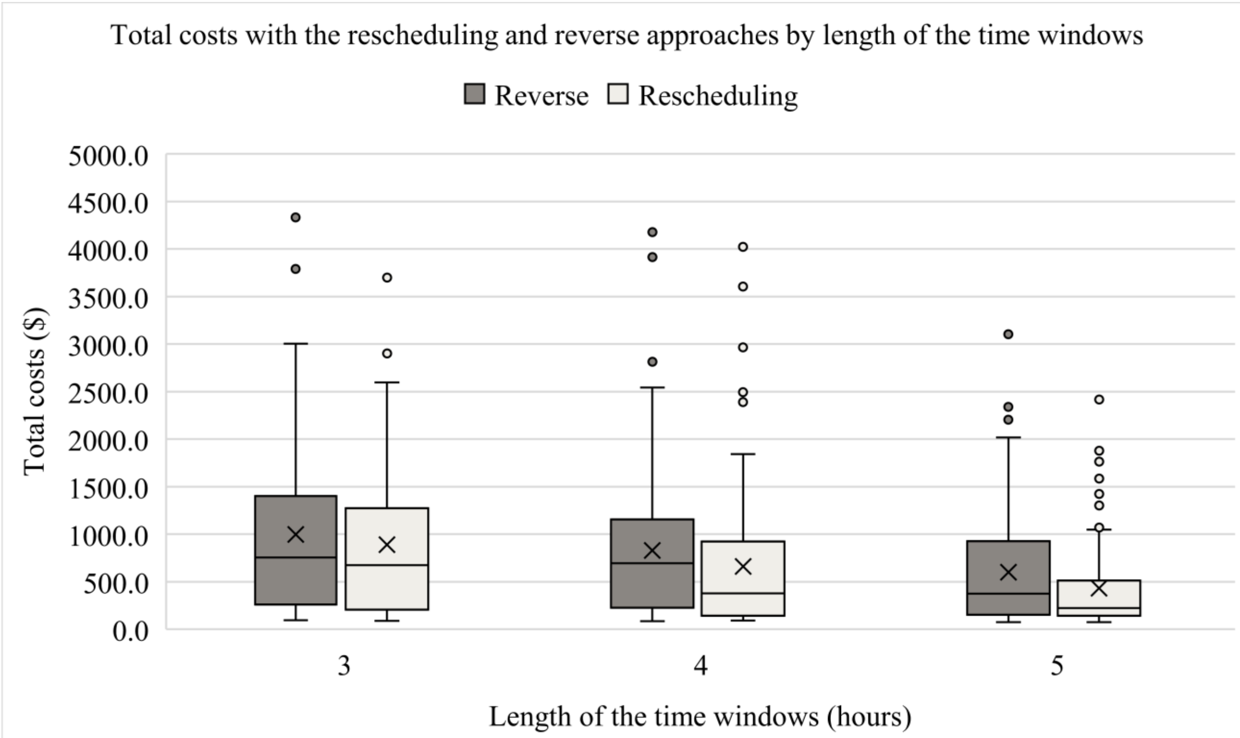

Figure 8 Disparity of the total costs with the rescheduling approach per length of time windows

Table 14 Impact of the length of the time windows on total costs

Approach	Length of the time windows (h)	3	4	5	TOTAL
	Number of tests	104	102	104	310
Rescheduling	Average ($)	890	662	433	662
	Standard deviation ($)	837	737	466	720
	Variance	700996	542484	216852	518362
	Standard Error Mean	82.1	72.92	45.66	
Reverse	Average ($)	998	830	599	809
	Standard deviation ($)	920	827	593	806
	Variance	847279	683719	351449	650004
	Standard Error Mean	90.26	81.82	58.13	
Difference between rescheduling and reverse	Average ($)	108	168	166	147
	Standard deviation ($)	297	339	280	306
	Variance	87933	114923	78624	93864

As observed in Figure 8, the larger the time windows size, the smaller the total costs. The worst performance was observed with three-hour time windows and the reverse approach (highest disparity and average). The best performance was observed with five-hour time windows and the rescheduling approach (smallest disparity and average). With the rescheduling approach, we observed an average decrease in total costs of 25% going from three-hour time windows to four-hour time windows (228$ difference), 34% going from four-hour time windows (229$ difference) and 51% going from three-hour time windows to five-hour time windows (457$ difference). Overall, the standard deviations and variances calculated for the tests analyzed were high for both methods and all lengths of the time windows, but larger time windows reduced their values. Those variations explain the great disparity observed in Figure 8.

Table 15 compares the total costs obtained with the rescheduling approach for each time window length. We used a t-test and p-value to identify if the differences were statistically significant.

Table 15 Independent sample t-test results comparing each length of the time windows

Comparison	t	df	p-value
3 hours vs. 4 hours	2.0753	201	0.0392
4 hours vs. 5 hours	4.8611	161	0.0086
3 hours vs. 5 hours	2.6588	170	0.0001

According to the t-test results and p-value, there is a large difference between each comparison of the length of the time windows (all t-tests > 2), and this difference is considered statistically significant (p-value < 0.05). Hence, we can conclude that the length of the time windows affected the total costs.

In sum, when looking at the results by length of the time window, we can observe a significant number of tests reducing the total costs when using the rescheduling approach. Also, having wider time windows have a more substantial impact on the overall cost decrease. This conclusion confirms the results observed in Braekers et al. (2016), Budak & Chen (2020) and Ouertani et al. (2019).

7. Conclusion and Future Considerations

In conclusion, this research provides a rescheduling approach that acknowledges caregivers' delays and earliness throughout their day when providing home health care. Delays or earliness can be due to traffic on the road, appointments lasting longer or shorter than expected, etc. Both optimization models, the initial assignment one and the rescheduling one, are formulated as Mixed-Integer Linear Programming models and solved using the commercial solver CPLEX. In the first optimization model, we find the initial Routing and Scheduling (RS) plan, where each patient that needs care on a day is assigned to a caregiver. This assignment is based on minimizing the total cost of travel time and overtime from caregivers, the cost of exceeding patients' time windows (maximizing patients' satisfaction) and the costs of imbalanced workloads among caregivers. After each patient visit, the rescheduling model is launched to ensure that each delay or earliness is captured. In the second optimization model, patients are rescheduled based on the current time and caregiver position. This rescheduling process aims to minimize travel time and overtime for caregivers and the penalties associated with exceeding patients' time windows while considering delays and earliness.

The rescheduling approach was tested on 310 instances. The results showed a decrease in total cost in 48.39% of the cases by an average of 349$ per test, no change in 36.45% of the cases and an increase in 15.16% of the cases by 147$ per test. Overall, the total costs decreased by 14% (an average of 147$ per test with a standard deviation of 306$) when using the rescheduling approach. High standard deviation and variance were also observed, which impacted the disparity of the results. A large difference was observed between the rescheduling and reverse approaches, and this difference has been shown to be statistically significant (p-value < 0.05). Hence, we were able to assume that the rescheduling approach affected the total costs. The length of the time windows also affected the total costs (p-value < 0.05). We noticed that the longer the time windows, the smaller the total costs. With the rescheduling approach, we observed an average decrease in total costs of 25% going from three-hour time windows to four-hour time windows (228$ difference), 34% going from four-hour time windows (229$ difference) and 51% going from three-hour time windows to five-hour time windows (457$ difference).

This thesis fits into the literature by covering three different aspects: (1) different time windows, (2) daily delays, and (3) the integration of patients' preferences for the Home Health Care Routing and Scheduling Problem (HHCRSP). It can serve the Home Health Care (HHC) industry by helping caregivers make decisions on their RS when they face delays and earliness throughout their day. It benefits patients as their preferences are being considered when the rescheduling model is launched after delays or earliness occur. This model could also profit the transport and delivery industries as they face similar challenges when time uncertainties happen. Rescheduling instantly the next trips could serve them as they also need to satisfy customers' preferences.

This approach also presents some limitations:

- It would only apply to settings where caregivers see multiple patients with small appointment durations daily. Otherwise, rescheduling patients throughout the day would not apply.
- It would only apply to settings where caregivers have all the required skills to treat all patients (for example, an in-home physiotherapy clinic where all patients have similar needs). If caregivers had different skill sets and patients had different needs, the model would need to be modified to include these aspects. Adding hard constraints to respect the skill set assignment and new variables would enable this implementation.
- We only consider small instances in this study. Currently, it would limit this approach to small institutions. In order to provide this method to larger institutions, the number of caregivers and patients would need to be increased. Using a heuristic or metaheuristic to solve the assignment problem could help solve larger instances. The assignment problem could include more patients and caregivers from the same area. It would help address the increasing demands of HHC services every day in Canada (Canadian Medical Association, 2021).
- Finally, we consider that the caregivers must go back to the medical at the end of their day. If the caregivers do not have anything to return to the medical centre (e.g., medical devices, drugs, etc.), the model could be changed so that caregivers can return home at the end of the day. Modifying the sets and indices would enable this change.

As for future research avenues, many ideas to improve HHC services might come to mind. First, this thesis relies on artificial data. In order to be implemented, it would be necessary to test this approach with actual data and collaborate with HHC institutions. It would provide real-life results and improvements. Second, including time-dependent traffic to represent caregivers' reality while on the road could also add to this research. This integration would assume future traffic delays in peak hours and then increase the travel time at specific times. Third, adding constraints to respect the continuity of care would also be an interesting way forward. Continuity of care in HHCRSP is gaining popularity as it has shown increased patient satisfaction (Di Mascolo et al., 2021). It could be implemented by adding different variables to identify what type of continuity of care (always, partial, never) should be followed for each patient (Carello et al., 2018). Fourth, an app could be developed and then utilized by caregivers while they are on the roads. As new RS are available instantly, having an app would facilitate the use of the rescheduling models. Caregivers would be able to access their new RS easily on their phones. Further research is necessary to include all of these considerations into the problem.

Appendix 1: Travel Time to Cover the Ottawa Region

Based on Google maps, when there is no traffic, driving from Vars (Ottawa's southeast point) to Kinburn (Ottawa's northwest point) takes about 53 minutes on highway 417 or 75 minutes taking highways 416 and 417. From Cumberland (Ottawa's northeast point) to Pierce Corners (Ottawa's southwest point), it takes about 49 minutes on highways 416 and 417 and up to 61 minutes on regional roads without traffic. The coordinates defined to cover the Ottawa region allow some time for traffic.

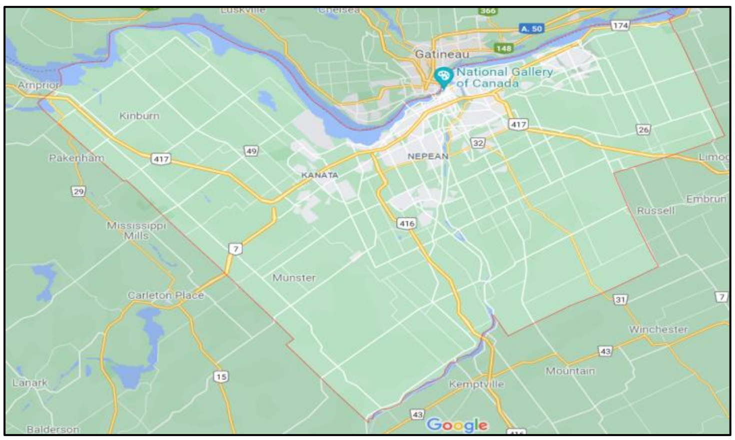

Figure 9 Map of the Ottawa Region based on Google maps

Figure 10 Longest distance to cover the Ottawa region

Appendix 2: Rescheduling Example with 15 patients and Two Caregivers

Caregiver 1’s day

Complete visit 1 (patient 9) with 12 minutes delay. The current time is minute 75. The following patients are rescheduled as below.

Table 16 Caregiver 1 – Visit 1 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	1	2	118	47	165	10	19	319					-18	23	0
2	2	4	175	55	230	25	19	319					-24	15	0
3	4	6	315	31	346	20	87	387					-20	-10	0
4	6	5	379	46	425	12	154	454					-14	-29	0
5	5	3	437	47	484	36	137	437					-2	-30	0
6	3	N1	545	31	576	24	293	593					-24	-2	0
	N1	1				43							18	-1	
	N1								230	180	360	0	0	0	

Complete visit 2 (patient 7) with 3 minutes delay. The current time is minute 168. The following patients are rescheduled as below.

Table 17 Caregiver 1 – Visit 2 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	1	2	178	55	233	25	19	319					-24	15	0
2	2	4	269	31	300	27	87	387					-20	-10	0
3	4	3	395	47	442	12	137	437					-2	-30	0
4	3	5	454	46	500	29	154	454					-14	-29	0
5	5	N1	529	31	560	24	293	593					-24	-2	0
	N1	1				10							-18	23	
	N1								300	180	360	0	0	0	

Complete visit 3 (patient 13) with 30 minutes delay. The current time is minute 263. The caregiver takes their lunch. The following patients are rescheduled as below.

Table 18 Caregiver 1 – Visit 3 completed

Patient i	**l (Start location)**	**m (End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	2	348	31	379	27	87	387					-20	-10	0
2	2	3	406	47	453	12	137	437					-2	-30	0
3	3	4	465	46	511	29	154	454					-14	-29	11
4	4	N1	545	31	576	24	293	593					-24	-2	0
	N1	1				25							-24	15	
	N1								263	263	360	0	0	0	

Complete visit 4 (patient 11) with 14 minutes delay. The current time is minute 393. The following patients are rescheduled as below.

Table 19 Caregiver 1 – Visit 4 completed

Patient i	**l (Start location)**	**m (End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	2	420	47	467	12	137	437		-2	-30	0
2	2	3	479	46	525	29	154	454		-14	-29	25
3	3	N1	554	31	585	24	293	593		-24	-2	0
	N1	1				27				-20	-10	
	N1								9	0	0	

Complete visit 5 (patient 5) with -9 minutes delay. The current time is minute 458. The following patients are rescheduled as below.

Table 20 Caregiver 1 – Visit 5 completed

Patient i	**l (Start location)**	**m (End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	2	470	46	516	29	154	454		-14	-29	16
2	2	N1	545	31	576	24	293	593		-24	-2	0
	N1	1				12				-2	-30	
	N1								0	0	0	

Complete visit 6 (patient 2) with -6 minutes delay. The current time is minute 510. The following patients are rescheduled as below. The rescheduling is stopped since only one patient is left on the list. Once the appointment is completed, the caregiver goes back to the medical centre.

Table 21 Caregiver 1 – Visit 6 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	$over_k$	xPos	yPos	ot_{ik}
1	1	N1	539	31	570	24	293	593		-24	-2	0
	N1	1				29				-14	-29	
	N1								0	0	0	

Caregiver 2's day

Complete visit 1 (patient 4) with 19 minutes delay. The current time is minute 102. The following patients are rescheduled as below.

Table 22 Caregiver 2 – Visit 1 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	3	4	120	28	148	5	35	335					18	12	0
2	4	2	153	53	206	15	126	426					14	15	0
3	2	1	221	30	251	20	191	491					23	27	0
4	1	5	341	30	371	8	41	341					29	8	0
5	5	6	418	19	437	13	319	619					22	12	0
6	6	7	450	36	486	7	237	537					29	1	0
7	7	N2	493	53	546	25	193	493					25	-5	0
	N2	3				18							14	-6	
	N2								251	180	360	0	0	0	

Complete visit 2 (patient 12) with 25 minutes delay. The current time is minute 173. The following patients are rescheduled as below.

Table 23 Caregiver 2 – Visit 2 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	3	2	185	30	215	20	41	341					29	8	0
2	2	1	235	30	265	15	191	491					23	27	0
3	1	4	340	53	393	9	126	426					14	15	0
4	4	5	402	19	421	13	319	619					22	12	0
5	5	6	450	36	486	7	237	537					29	1	0
6	6	N2	493	53	546	25	193	493					25	-5	0
	N2	3				12							18	12	
	N2								280	180	360	0	0	0	

Complete visit 3 (patient 3) with 4 minutes delay. The current time is minute 219. The following patients are rescheduled as below.

Table 24 Caregiver 2 – Visit 3 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	1	2	239	30	269	15	191	491					23	27	0
2	2	3	344	53	397	9	126	426					14	15	0
3	3	4	406	19	425	13	319	619					22	12	0
4	4	5	438	36	474	7	237	537					29	1	0
5	5	N2	481	53	534	25	193	493					25	-5	0
	N2	1				20							29	8	
	N2								269	219	360	0	0	0	

Complete visit 4 (patient 14) with -4 minutes delay. The current time is minute 265. The caregiver takes their lunch. The following patients are rescheduled as below.

Table 25 Caregiver 2 – Visit 4 completed

Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	b_k	BE_k	BL_k	$over_k$	xPos	yPos	ot_{ik}
1	1	2	340	53	393	9	126	426					14	15	0
2	2	3	402	19	421	13	319	619					22	12	0
3	3	4	434	36	470	7	237	537					29	1	0
4	4	N2	477	53	530	25	193	493					25	-5	0
	N2	1				15							23	27	
	N2								265	265	360	0	0	0	

Complete visit 5 (patient 15) with 20 minutes delay. The current time is minute 413. The following patients are rescheduled as below.

Table 26 Caregiver 2 – Visit 5 completed

Patient i	l **(Start location)**	m **(End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	3	422	19	441	17	319	619		22	12	0
2	3	2	475	53	528	7	193	493		25	-5	0
3	2	N2	535	36	571	29	237	537		29	1	0
	N2	1				9				14	15	
	N2								0	0	0	

Complete visit 6 (patient 10) with 30 minutes delay. The current time is minute 471. The following patients are rescheduled as below.

Table 27 Caregiver 2 – Visit 6 completed

Patient i	l **(Start location)**	m **(End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	2	488	53	541	7	193	493		25	-5	0
2	2	N2	548	36	584	29	237	537		29	1	11
	N2	1				17				22	12	
	N2								13	0	0	

Complete visit 7 (patient 8) with -6 minutes delay. The current time is minute 535. The following patients are rescheduled as below. The rescheduling is stopped since only one patient is left on the list. Once the appointment is completed, the caregiver goes back to the medical centre.

Table 28 Caregiver 2 – Visit 7 completed

Patient i	l **(Start location)**	m **(End location)**	s_{ik}	V_i	**End visit**	T_{lm}	PE_i	PL_i	$over_k$	**xPos**	**yPos**	ot_{ik}
1	1	N2	542	36	578	29	237	537		29	1	5
	N2	1				7				25	-5	
	N2								7	0	0	

Table 29 Rescheduling results including delays and earliness

Caregiver k	Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	Lunch k	$over_k$	xPos	yPos	ot_{ik}
16	1	9	7	42	33	75	43	42	342			18	-1	-300
16	2	7	13	118	50	168	10	19	319			-18	23	-201
16	3	13	11	178	85	263	25	19	319			-24	15	-141
16	4	11	5	348	45	393	27	87	387			-20	-10	-39
16	5	5	2	420	38	458	12	137	437			-2	-30	-17
16	6	2	6	470	40	510	29	154	454			-14	-29	16
16	7	6	16	539	31	570	24	293	593			-24	-2	-54
17	1	4	12	28	74	102	18	28	328			14	-6	-300
17	2	12	3	120	53	173	12	35	335			18	12	-215
17	3	3	14	185	34	219	20	41	341			29	8	-156
17	4	14	15	239	26	265	15	191	491			23	27	-252
17	5	15	10	340	73	413	9	126	426			14	15	-86
17	6	10	8	422	49	471	17	319	619			22	12	-197
17	7	8	1	488	47	535	7	193	493			25	-5	-5
17	8	1	17	542	36	578	29	237	537			29	1	5
16		16	9				18			263	0	0	0	
17		17	4				15			265	7	0	0	

Table 30 Reversed results including delays and earliness

Caregiver k	Patient i	l (Start location)	m (End location)	s_{ik}	V_i	End visit	T_{lm}	PE_i	PL_i	Lunch k	$over_k$	xPos	yPos	ot_{ik}
16	1	9	7	42	33	75	43	42	342			18	-1	-300
16	2	7	13	118	50	168	10	19	319			-18	23	-201
16	3	13	6	240	85	325	17	19	319			-24	15	-79
16	4	6	11	342	31	373	9	293	593			-24	-2	-251
16	5	11	5	382	45	427	27	87	387			-20	-10	-5
16	6	5	2	454	38	492	12	137	437			-2	-30	17
16	7	2	16	504	40	544	32	154	454			-14	-29	50
17	1	4	3	28	74	102	21	28	328			14	-6	-300
17	2	3	14	123	34	157	20	41	341			29	8	-218
17	3	14	12	240	26	266	16	191	491			23	27	-251
17	4	12	15	282	53	335	5	35	335			18	12	-53
17	5	15	10	340	73	413	9	126	426			14	15	-86

17	6	10	1	422	49	471	13	319	619			22	12	-197
17	7	1	8	484	36	520	7	237	537			29	1	-53
17	8	8	17	527	47	574	25	193	493			25	-5	34
16							18			180	0	0	0	
17							15			180	0	0	0	

Appendix 3: Results for each Instance Set

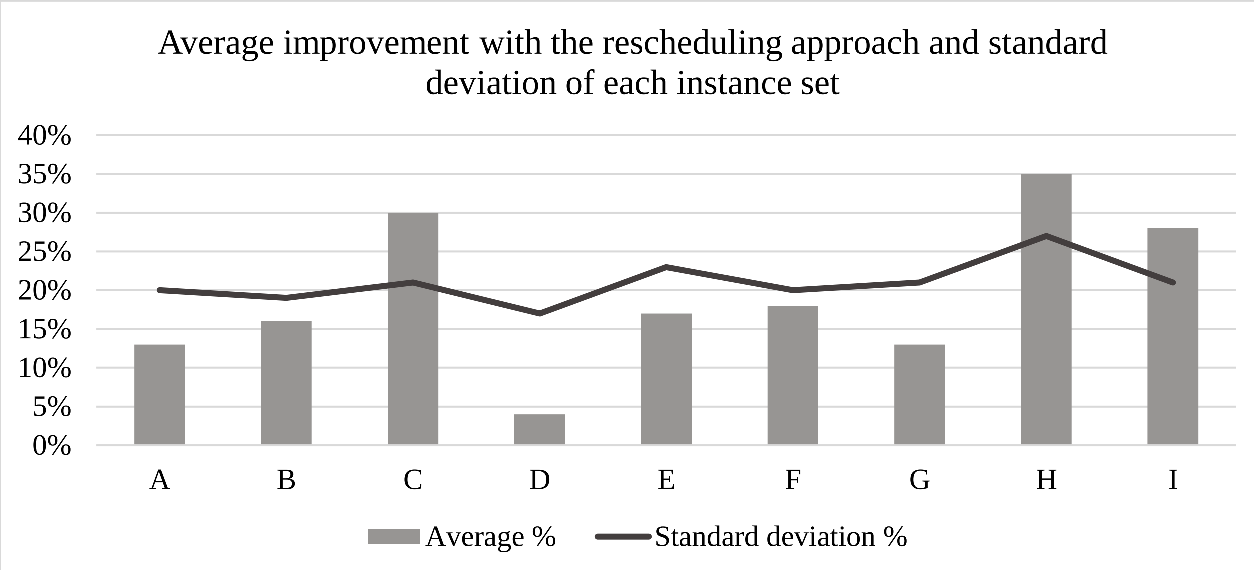

Figure 11 Average and standard deviation of improvement with the rescheduling approach for each instance set

Table 31 Instance Set A

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	2225	1162	-1063	48%
2	916	336	-580	63%
3	948	928	-20	2%
4	5745	5180	-565	10%
5	1121	1121	0	0%
6	2011	1980	-31	2%
7	3428	3319	-109	3%
8	3192	2959	-233	7%
9	3612	3047	-565	16%
10	789	789	0	0%
11	3789	3789	0	0%
12	1391	1403	12	-1%
13	2166	2166	0	0%
14	1339	1339	0	0%
15	2240	1385	-855	38%
		Average	**-267**	**13%**
		Standard deviation	**362**	**20%**
		Maximum	**-1063**	**63%**
		Minimum	**12**	**-1%**

Table 32 Instance Set B

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	1387	1294	-94	7%
2	546	316	-230	42%
3	1309	1298	-11	1%
4	2284	2440	156	-7%
5	859	859	0	0%
6	1354	1133	-221	16%
7	1854	1241	-612	33%
8	1525	1144	-382	25%
9	1392	1252	-140	10%
10	1047	418	-629	60%
11	1318	993	-325	25%
12	1828	1211	-618	34%
13	942	941	-1	0%
14	1307	1307	0	0%
15	1822	1822	0	0%
		Average	**-207**	**16%**
		Standard deviation	**256**	**19%**
		Maximum	**-629**	**60%**
		Minimum	**156**	**-7%**

Table 33 Instance Set C

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	1609	1662	53	-3%
2	1516	1189	-327	22%
3	1309	551	-759	58%
4	1119	1079	-41	4%
5	1116	966	-150	13%
6	2590	1394	-1197	46%
7	836	521	-315	38%
8	1861	1109	-753	40%
9	1092	1092	0	0%
10	1496	994	-502	34%
11	488	282	-206	42%
12	1297	537	-760	59%
13	613	401	-212	35%

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
14	395	332	-63	16%
15	1895	935	-961	51%
		Average	**-413**	**30%**
		Standard deviation	**387**	**21%**
		Maximum	**-1197**	**59%**
		Minimum	**53**	**-3%**

Table 34 Instance Set D

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Decrease with the rescheduling approach (%)
1	2570	2973	403	-16%
2	3331	3243	-88	3%
3	4056	3456	-600	15%
4	6869	6102	-768	11%
5	2447	2965	518	-21%
6	2434	2106	-328	13%
7	2363	1981	-383	16%
8	2804	2552	-252	9%
9	1776	1076	-700	39%
10	2696	2879	183	-7%
11	3551	2996	-555	16%
12	1579	2020	441	-28%
13	2909	2769	-140	5%
14	2597	2427	-170	7%
15	4769	4562	-208	4%
		Average	**-176**	**4%**
		Standard deviation	**410**	**17%**
		Maximum	**-768**	**39%**
		Minimum	**518**	**-28%**

Table 35 Instance Set E

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	1782	1873	92	-5%
2	2555	3098	543	-21%
3	2962	1957	-1005	34%

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
4	5612	4462	-1150	20%
5	1682	1607	-75	4%
6	2633	2535	-98	4%
7	4414	4268	-146	3%
8	3114	1510	-1604	52%
9	1836	653	-1182	64%
10	2256	2155	-101	4%
11	2692	1450	-1241	46%
12	5689	5449	-240	4%
13	2381	1936	-445	19%
14	2687	1993	-694	26%
15	1376	1333	-43	3%
		Average	**-492**	**17%**
		Standard deviation	**615**	**23%**
		Maximum	**-1604**	**64%**
		Minimum	**543**	**-21%**

Table 36 Instance Set F

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	345	335	-10	3%
2	3257	2569	-688	21%
3	1679	1087	-592	35%
4	2094	2159	65	-3%
5	2094	1339	-755	36%
6	3384	2496	-888	26%
7	609	396	-213	35%
8	774	914	141	-18%
9	2641	1528	-1113	42%
10	2856	2302	-553	19%
11	1076	1029	-47	4%
12	743	743	0	0%
13	3143	2765	-377	12%
14	486	445	-41	8%
15	2603	1253	-1350	52%
		Average	**-428**	**18%**
		Standard deviation	**464**	**20%**

		Maximum	**-1350**	**52%**
		Minimum	**141**	**-18%**

Table 37 Instance Set G

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	3479	2832	-647	19%
2	640	696	56	-9%
3	595	495	-100	17%
4	589	365	-224	38%
5	1331	1368	38	-3%
6	1779	1417	-361	20%
7	485	463	-22	5%
8	3283	1532	-1752	53%
9	543	723	180	-33%
10	1395	1267	-128	9%
11	576	582	6	-1%
12	1755	1680	-75	4%
13	2237	1956	-280	13%
14	1730	1218	-512	30%
15	1643	1175	-468	28%
		Average	**-286**	**13%**
		Standard deviation	**468**	**21%**
		Maximum	**-1752**	**53%**
		Minimum	**180**	**-33%**

Table 38 Instance Set H

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	1073	357	-716	67%
2	501	341	-160	32%
3	1257	862	-395	31%
4	1786	1794	8	0%
5	1075	1075	0	0%
6	713	395	-318	45%
7	2145	428	-1717	80%
8	932	374	-558	60%
9	1222	899	-323	26%
10	1611	1240	-371	23%
11	2046	2053	7	0%

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
12	1876	346	-1530	82%
13	1485	1125	-360	24%
14	1472	1216	-256	17%
15	2230	1410	-820	37%
		Average	**-501**	**35%**
		Standard deviation	**517**	**27%**
		Maximum	**-1717**	**82%**
		Minimum	**8**	**0%**

Table 39 Instance Set I

Instances	Objective function result (Reverse approach)	Objective function result (Rescheduling approach)	Difference	Improvement with the rescheduling approach (%)
1	709	429	-280	39%
2	1568	765	-802	51%
3	493	493	0	0%
4	357	357	0	0%
5	576	379	-198	34%
6	1258	480	-778	62%
7	2372	1930	-442	19%
8	1136	840	-297	26%
9	945	880	-65	7%
10	992	507	-485	49%
11	852	425	-428	50%
12	634	393	-240	38%
13	1677	1257	-420	25%
14	767	845	78	-10%
15	1099	792	-307	28%
		Average	**-311**	**28%**
		Standard deviation	**261**	**21%**
		Maximum	**-778**	**62%**
		Minimum	**78**	**-10%**

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