

Article

Home Health Care Routing and Scheduling Problem with Soft Time Windows and Perishable Medicines

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Abstract

This research investigates the home health care routing and scheduling problem with soft time windows and perishable medicines (HHCRSP-STW-PM), where care crews must serve patients over multiple periods while accounting for skill-based assignments, medicine perishability, and flexible service times. The objective minimizes total travel and penalty costs for early or late services. We formulate a mixed integer linear program (MILP) model to optimally solve small instances and develop an effective greedy randomized adaptive search procedure (GRASP) to address large instances. GRASP includes a tailored construction heuristic with problem-specific local search operators in the local search phase. Numerical experiments conducted on newly generated instances demonstrate that while the MILP model provides optimal solutions for small instances, only GRASP is able to handle large-scale instances within a reasonable computational time. Sensitivity analyses allow us to examine the impact of the approach's parameters, perishability of medicine, soft time windows, and care crew resources.

Keywords: home health care; perishable medicines; routing and scheduling problem; soft time windows; metaheuristic

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1. Introduction

With aging populations for many countries in the world, especially Asia, the demand for medical services is increasing, particularly for home health care (HHC), which delivers long-term treatment services directly at patients' private locations and thus alleviates the burden on medical centers (MCs) [1]. The COVID-19 pandemic further underscored the critical role of HHC in modern healthcare systems. The global HHC market size is projected to be 335.22 billion USD in 2025 and to hit 503.12 billion USD by 2030 [2]. HHC provides significant advantages in healthcare systems such as alleviating workloads at MCs, offering convenient care for elderly patients, and reducing healthcare costs and times [3].

HHC services encompass physical and occupational therapy, palliative care, and home medical infusions, which are crucial for pain management and symptom relief. Home-based infusions offer clear benefits, such as reducing health risks for intravenous immunoglobulin patients [4] and enhancing the quality of life for patients with chronic conditions like

congenital nephrotic syndrome [5]. However, challenges arise when administering time-sensitive medications, including albumin, insulin, apomorphine, and meropenem, which require strict storage conditions and limited shelf lives [6]. Studies addressing these medications in HHC services often overlook the perishability of medications like French chemotherapy [7] and blood or bio-sample collections [8]. This gap is particularly critical for periodic treatments with perishable medications such as chemotherapy [9], vaccination distribution [10], or blood collection and delivery [11,12]. In fact, scheduling models have not fully incorporated their perishability constraints.

From an operations research perspective, HHC systems must optimize routing and scheduling to serve patients in their dispersed locations while meeting various requirements, referred to as the home health care scheduling and routing problem (HHCRSP) [13]. HHCRSP focuses on assigning qualified care crews to serve all patients while minimizing travel costs and improving service quality [1]. Many HHC services involve recurring treatments that are often planned over multiple periods (e.g., weekly) to balance patient needs and workforce availability [14,15]. While single-period HHCRSP only focuses on meeting service requests and assigning care-crews within a single time frame, multi-period planning must additionally account for care-crew working regulations and patients' evolving care plans across multiple periods. This increases the complexity of generating feasible plans that respect both regulatory constraints and patient needs over time [16]. Additionally, skill-based assignments are crucial for ensuring proper treatment [14], while patient availability must be considered in scheduling decisions [17]. Classical HHC systems enforce hard time windows for patient services [18,19], where the services must strictly adhere to predefined schedules. The concept of soft time windows allows for controlled flexibility with penalties for early or late services, making them more practical under resource limitations and complex scheduling constraints [15,20].

This paper introduces an extension of HHCRSP by incorporating soft time windows and medicine perishability constraints. In the existing works, the perishable item is usually transported under strict timing requirements, and the routing decisions are often designed to ensure that the item can be returned or delivered within a limited time. However, the use of perishable medicines in HHC services has a different practical meaning. The care crew leaves the MC with prescribed medicines and must administer them to patients before their shelf lives expire. Thus, the model should not only satisfy patient time windows and care crew working hours, but also ensure that each medicine remains valid when it is used. Varas et al. [21] assume that caregivers must return immediately to the medical center with a perishable biological sample after serving a patient. In contrast, our study relaxes this assumption by allowing care crews to serve additional patients before returning to the MC, as long as all medicines are administered within their effective durations. This difference provides more routing flexibility while still maintaining the quality of perishable medicines. Furthermore, we consider multi-period planning and skill-based crew assignments to enhance the realism and applicability of HHC operations.

Based on this setting, the theoretical contribution is to investigate an HHCRSP variant that jointly considers soft time windows, medicine perishability, multi-period service requests, and skill-based care crew assignments. The routing plan is affected not only by patient availability and care crew working hours, but also by the shelf life of the medicine required by each patient. Our main contributions are summarized as follows.

- We introduce the home health care routing and scheduling problem with soft time windows and perishable medicines (HHCRSP-STW-PM), aiming to minimize travel costs and penalty costs from early and late services.

- We formulate a mixed-integer linear programming (MILP) model for small instances and develop a greedy randomized adaptive search procedure (GRASP) for large instances. GRASP includes a tailored construction heuristic and problem-specific local search operators. Moreover, an effective procedure for evaluating the tours' start times is proposed to update the objective function.
- We evaluate the performance of the MILP model and GRASP on HHCRSP-STW-PM instances. While the model finds optimal solutions for small instances by using the GUROBI solver, only GRASP can solve large instances within a reasonable computational time.
- We conduct sensitivity analyses to assess the impact of medicine perishability and soft time windows, offering managerial insights to optimize and stabilize HHC operations.

The rest of this paper runs as follows. Section 2 reviews related works on HHCRSP, perishable medicines, and GRASP. Section 3 formally defines the problem and presents a mathematical model. Section 4 proposes a GRASP approach, incorporating an effective construction heuristic and neighborhood operators. Section 5 presents numerical experiments to assess the performance of GRASP and analyzes the impact of medicine deterioration and the penalty of soft time windows. Section 6 summarizes the key contributions and suggests directions for future research.

2. Literature Review

HHCRSP was first introduced by Begur et al. [22] to optimize caregiver routing for delivering HHC services to patients with specific medical needs. It can be viewed as an extension of the vehicle routing problem with time windows (VRPTW), with additional constraints such as skill compatibility, patient-specific requirements, and workforce limitations [1]. Despite these additional features, HHCRSP retains the main characteristics of VRPTW, including route optimization, time-window constraints, and workload balancing [21]. For comprehensive reviews of HHCRSP research, readers may refer to Cissé et al. [1] and Di Mascolo et al. [3].

2.1. Objective Functions in HHCRSP Variants

A major stream of HHCRSP research focuses on operational optimization. Early and standard models often aim to minimize total operational costs [23–25] or reduce travel and service times [26,27]. However, HHC planning is not only a cost-minimization problem, because patient satisfaction, caregiver workload, and service reliability are also important. Therefore, many studies incorporate caregiver and patient satisfaction [28–30], patient preferences [18,31], or service rates and profits [32,33].

While some studies use a single-objective formulation [26,33], multi-objective models are more common in recent studies [28,30,34,35]. For example, Kummer et al. [35] combine several cost and service components into a weighted objective function, while Braekers et al. [24] analyze the trade-off between operational costs and patient dissatisfaction using a bi-objective model. More recent studies further extend this direction. Liu et al. [36] consider total workload by weighting system time and physical load, while Ceschia et al. [37] combine several cost components and solve the resulting problem using simulated annealing. These studies show that service-level performance is an essential part of HHC optimization.

In our problem, this aspect is captured by combining travel cost with penalty costs for early and late services.

2.2. Operational Constraints and Multi-Period Planning

Another important stream studies operational constraints that make HHCRSP closer to real HHC practice. These constraints include skill compatibility between patients and caregivers [37–39], patient preferences such as time windows and additional services [27,40,41], caregiver working-time limits [42,43], and continuity of care over multiple periods [39,44]. Recent studies have also considered more complex HHC settings, such as multi-echelon healthcare systems [45], drone-assisted HHC systems [46], multiple or dynamic time windows [15], multi-skilled crews [47], and multi-service HHC systems [30]. These works indicate that the structure of HHC services has become increasingly rich. However, the perishability of treatment medicines has received much less attention in HHCRSP models, even though it directly affects route feasibility and service timing.

The planning horizon is another important modeling issue. Many HHCRSP models focus on a single period, such as daily planning [27,28,48], while others extend the planning horizon to one week [40,49]. Recently, Bazirha et al. [13] consider mixed patient sets with hard and soft time windows, Varas et al. [21] use multiple time windows with different services in a single day, Nasir and Kuo [15] consider multi-period services with dynamic time windows, and van Montfort et al. [50] split long visits into multiple tasks. These studies show that multi-period planning can better reflect recurring HHC services.

Our work follows this direction by considering patient requests over multiple periods, where patients may require services in different periods of the planning horizon.

2.3. Soft Time Windows and Perishability-Related Healthcare Logistics

Soft time windows are closely related to service-level optimization. While many studies use hard time windows to ensure that patients are served within fixed intervals [26,27], soft time windows allow limited early or late services with penalties [17,23,28,35]. These models provide more flexibility when resources are limited, while still reflecting patient dissatisfaction caused by time-window violations. Recent studies have further considered multiple time windows, where time windows can be either strict or relaxed depending on the service type [13,37]. These time-window settings are often combined with synchronization constraints, where multiple services must be performed in a fixed or dynamically determined sequence [15,30,37].

Existing studies have also considered perishable biological samples, medication refills, and other time-sensitive healthcare services. For example, Shahnejat-Bushehri et al. [51] and Varas et al. [21] discuss biological sample collection services, where care crews must return to the hospital after completing certain visits. Similarly, Nasir and Kuo [15] consider a HHCRSP context with multi-depot, multi-period, dynamic services, medication refill, and biological samples collections. These studies are relevant to perishable healthcare logistics because route feasibility depends on the time-sensitive nature of medical items. In contrast, few studies focus on perishable medicines transported from the MC to patients and required to be administered before expiration [37]. This creates a different routing logic: care crews are allowed to serve multiple patients before returning to the MC, provided the medicines remain valid for use.

In our study, soft time windows are used to balance operational flexibility and patient satisfaction, while the medicine shelf life imposes an additional hard timing restriction.

2.4. Solution Approaches for HHCRSP

From a methodological perspective, HHCRSP studies mainly use exact methods, matheuristics, and metaheuristics. Exact methods, such as branching-based algorithms [23,52] and Benders decomposition [29,45,53], are useful for solving small instances and validating mathematical models, but they face scalability limitations. Matheuristic

approaches, including Lagrangian relaxation [54,55] and multi-stage frameworks [21,56], improve scalability by combining mathematical programming with heuristic search. Meta-heuristics, such as genetic algorithms (GA) [35], simulated annealing (SA) [37], ant colony optimization (ACO) [28], and adaptive large neighborhood search (ALNS) [33], have also been widely adopted for larger and more constrained instances. GRASP has also shown good performance under limited computational resources [40,57].

Building on this stream, our study develops a GRASP algorithm with a construction heuristic and local search operators tailored to skill compatibility, soft time windows, and medicine-validity constraints.

To the best of our knowledge, the joint consideration of medicine perishability, soft time windows, multi-period service requests, and skill-based care crew assignments remains limited in the HHCRSP literature. Existing studies have addressed some of these elements separately, but their integration creates additional routing and scheduling challenges because service timing must satisfy patient preferences, care crew working hours, skill compatibility, and medicine shelf-life requirements at the same time. Therefore, the proposed model not only optimizes routing and scheduling decisions but also incorporates medicine perishability constraints and controlled flexibility in service times.

3. Problem Description and Mathematical Model

HHCRSP-STW-PM considers a network, including a medical center (MC) as the starting location 0, a dummy MC as the endpoint of each tour $0'$, and a set of η_C patients (denoted by $C = \{1, \dots, \eta_C\}$). The problem also involves a set of η_P care crews (denoted by $P = \{1, \dots, \eta_P\}$), who are responsible for serving all patient requests. The scheduling takes place over η_K periods (days), represented as $K = \{1, \dots, \eta_K\}$. The network is formally modeled as a graph $G = (N, A)$, where $N = \{0, 0'\} \cup C$ represents the set of all nodes, and A denotes the set of all possible arcs connecting them. Each arc $(i, j) \in A$ is associated with a travel time t_{ij} and a travel cost $c_{ij} = \gamma t_{ij}$, where γ is the travel unit cost.

Each care crew $p \in P$ is assigned a tour in each period $k \in K$ and operates within a predefined time horizon (e.g., the work shift), denoted by $[l'_{pk}, u'_{pk}]$. Additionally, each care crew $p \in P$ possesses a treatment skill level θ_p , which represents their ability to serve patients. Each patient $i \in C$ requires medical service that must be administered before the prescribed medicines expire. The shelf-life of medicines required by patient i (denoted by Γ_i) represents the time limit within which they must be used after leaving MC. Patients may require service across multiple periods depending on their demands. This is indicated by α_{ik} , where $\alpha_{ik} = 1$ if patient $i \in C$ requires service in period $k \in K$; otherwise, no visit is required for that patient in that period. Each patient also has a specific treatment requirement level β_i , which must be met by the care crew's treatment skill level (i.e., it satisfies $\theta_p \geq \beta_i$). The service time at each patient $i \in C$ is denoted by s_i . Each patient prefers to be served within a predefined time window $[l_{ik}, u_{ik}]$. However, early and late services are permitted, subject to penalty unit costs a and b , respectively. Table 1 summarizes the definitions of sets and parameters used in HHCRSP-STW-PM.

Our HHCRSP-STW-PM is NP-hard, which is an extension of VRPTW. Hence, our MILP formulation is limited to addressing small instances, as confirmed in our experiments later. We further consider some assumptions as follows.

- Each tour starts and ends at MC. Each care crew is only assigned to a single tour in each period. Moreover, their operations must be within their defined time windows.
- All patient requests are assumed to be known in advance and stable over the planning horizon. Each patient's required treatments are represented by α_{ik} . This assumption is reasonable for tactical or weekly planning, especially for patients with chronic diseases

or regular prescriptions, where treatment plans are usually determined before care crews are dispatched.

- All patient requests must be served in each period. Their medicines must be administered within their shelf-life time. In other words, the use of expired medicines is strictly prohibited.
- Travel times and service times are assumed to be deterministic and known in advance. Uncertain factors such as traffic conditions are ignored in this study.
- The care crew's treatment skill level must be equal to or higher than the required treatment level of the assigned patients.

Table 1. Definitions of sets and parameters.

Notation	Definition
$\{0, 0'\}$	Set of the starting and ending MCs in each tour, respectively
C	Set of η_C patients, denoted by $C = \{1, \dots, \eta_C\}$
N	Set of all nodes, including MC and all patients, denoted by $N = \{0, 0'\} \cup C$
K	Set of η_K periods, denoted by $K = \{1, \dots, \eta_K\}$
P	Set of η_P care crews, denoted by $P = \{1, \dots, \eta_P\}$
A	Set of all connected arcs, denoted by $A = \{(i, j) i \in N, j \in N, i \neq j\}$
α_{ik}	1 if patient $i \in C$ requests treatment at period $k \in K$; otherwise, 0
β_i	Required treatment skill level for patient $i \in C$
θ_p	Treatment skill level of care crew $p \in P$
s_i	Treatment time required for patient $i \in C$
t_{ij}	Travel time for arc $(i, j) \in A$
c_{ij}	Travel cost for arc $(i, j) \in A$
$[l_{ik}, u_{ik}]$	Preferred time window for patient $i \in C$ in period $k \in K$
$[l'_{pk}, u'_{pk}]$	Work shift time windows of care crew $p \in P$ in period $k \in K$
u_{0k}	MC's closing time in period $k \in K$
Γ_i	Shelf-life of the medicine used for treating patient $i \in C$
a	Unit penalty cost for early service
b	Unit penalty cost for late service

Figure 1 illustrates an example of the problem. The left side of the figure represents a network consisting of a medical center (MC) (node 0) and nine patients (nodes 1 to 9). Each patient has a required treatment skill level and specific request periods. The right side of the figure shows the construction of tours over three periods, served by three care crews with different skill levels (ranging from 1 to 3). For instance, in period 1, a subset of patients (nodes 1, 2, 3, 7, and 8) requests HHC services. Two care crews with a skill level of 3 are assigned to serve patients 1, 2, and 3, while another care crew with a skill level of 1 serves patients 7 and 8. Similarly, tours in the remaining periods are planned while ensuring that patient requirements are met.

To determine a solution for the problem in the mathematical model, we define a set of decision variables, as summarized in Table 2.

Table 2. List of decision variables.

Variables	Definition
x_{ijpk}	1 if arc $(i, j) \in A$ is used by care-crew $p \in P$ at period $k \in K$; otherwise, 0
y_{ipk}	1 if patient $i \in C$ is checked by care crew $p \in P$ at period $k \in K$ earlier than the time windows (i.e., $\tau_{ipk} < l_{ik}$); otherwise, 0
z_{ipk}	1 if patient $i \in C$ is checked by care crew $p \in P$ at period $k \in K$ later than the time window (i.e., $\tau_{ipk} > u_{ik}$); otherwise, 0
τ_{ipk}	Arrival time of care-crew $p \in P$ upon node $i \in N$ at period $k \in K$
λ_{ipk}	Penalty time of care-crew $p \in P$ for early visit patient $i \in C$ in period $k \in K$
μ_{ipk}	Penalty time of care-crew $p \in P$ for late visit patient $i \in C$ in period $k \in K$

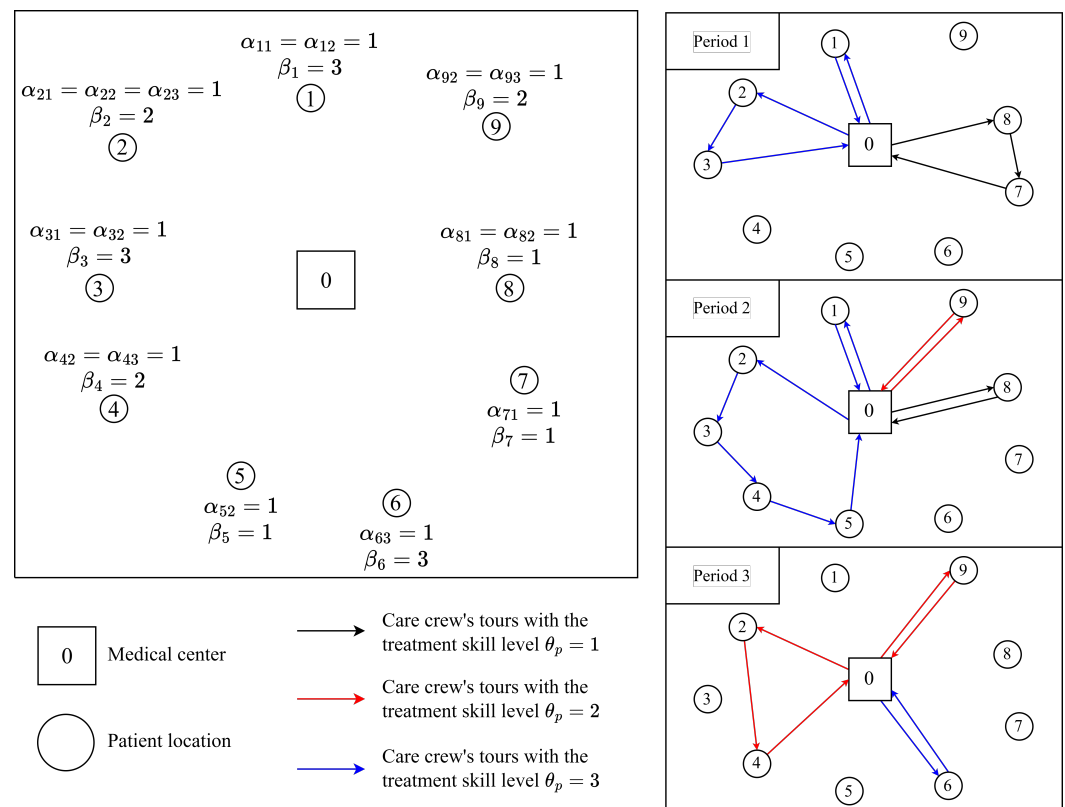


Figure 1. An illustrative example of HHCRSP-STW-PM.

The MILP model is then presented as follows.

$$\text{Minimize } \sum_{(i,j) \in N} \sum_{p \in P} \sum_{k \in K} c_{ij} x_{ijpk} + \sum_{i \in N} \sum_{p \in P} \sum_{k \in K} (a \lambda_{ipk} + b \mu_{ipk}) \quad (1)$$

The objective function (1) minimizes the total cost, which consists of two components: total travel cost and penalty costs for early and late services.

$$\sum_{(i,j) \in A} \sum_{p \in P} x_{ijpk} = \alpha_{jk} \quad \forall j \in C, k \in K \quad (2)$$

$$\sum_{(i,j) \in A} x_{ijpk} \beta_j \leq \theta_p \quad \forall j \in C, p \in P, k \in K \quad (3)$$

$$\sum_{(0,j) \in A} x_{0jpk} \leq 1 \quad \forall k \in K, p \in P \quad (4)$$

$$\sum_{(j,0') \in A} x_{j0'pk} \leq 1 \quad \forall k \in K, p \in P \quad (5)$$

$$\sum_{(0,j) \in A} x_{0jpk} - \sum_{(j,0') \in A} x_{j0'pk} = 0 \quad \forall k \in K, p \in P \quad (6)$$

$$\sum_{(i,j) \in A} x_{ijpk} - \sum_{(j,i) \in A} x_{jipk} = 0 \quad \forall j \in N, k \in K, p \in P \quad (7)$$

Constraint (2) ensures that each patient is served during the required periods. Constraint (3) guarantees that the assigned care crew has the necessary qualifications to treat the visited patients. Constraints (4) and (5) ensure that each care crew starts and ends the tour at MC at most once per period, respectively. Constraint (6) ensures that the

departed care crew will return later in the same period. Constraint (7) enforces the flow conservation of tours.

$$\tau_{jpk} \leq \tau_{ipk} + s_i + t_{ij} + u_{0k}(1 - x_{ijpk}) \quad \forall (i, j) \in A, p \in P, k \in K \quad (8)$$

$$\tau_{jpk} \geq \tau_{ipk} + s_i + t_{ij} - u_{0k}(1 - x_{ijpk}) \quad \forall (i, j) \in A, p \in P, k \in K \quad (9)$$

$$l'_{pk} \leq \tau_{ipk} \leq u'_{pk} \quad \forall i \in N, p \in P, k \in K \quad (10)$$

$$\tau_{jpk} - \tau_{0pk} \leq \Gamma_j + u_{0k}(1 - \sum_{(i,j) \in A} x_{ijpk}) \quad \forall j \in C, p \in P, k \in K \quad (11)$$

$$l_{ik} - \tau_{ipk} \leq \lambda_{ipk} \quad \forall i \in C, p \in P, k \in K \quad (12)$$

$$l_{ik} - \tau_{ipk} \geq \lambda_{ipk} - u_{0k}(1 - y_{ipk}) \quad \forall i \in C, p \in P, k \in K \quad (13)$$

$$\lambda_{ipk} \leq u_{0k}y_{ipk} \quad \forall i \in C, p \in P, k \in K \quad (14)$$

$$\tau_{ipk} + s_i - u_{ik} \leq \mu_{ipk} \quad \forall i \in C, p \in P, k \in K \quad (15)$$

$$\tau_{ipk} + s_i - u_{ik} \geq \mu_{ipk} - u_{0k}(1 - z_{ipk}) \quad \forall i \in C, p \in P, k \in K \quad (16)$$

$$\mu_{ipk} \leq u_{0k}z_{ipk} \quad \forall i \in C, p \in P, k \in K \quad (17)$$

Constraints (8) and (9) determine the service start time at each node. Constraint (10) ensures that each tour operates within the assigned care crew's work shift. Constraint (11) guarantees that care crews visit patients before their prescribed medicines expire. Constraints (12)–(14) compute the penalty for early visits, while Constraints (15)–(17) determine the penalty for late visits.

$$x_{ijpk} \in \{0, 1\} \quad \forall (i, j) \in A, p \in P, k \in K \quad (18)$$

$$y_{ipk}, z_{ipk} \in \{0, 1\} \quad \forall i \in N, p \in P, k \in K \quad (19)$$

$$\tau_{ipk}, \lambda_{ipk}, \mu_{ipk} \geq 0 \quad \forall i \in N, p \in P, k \in K \quad (20)$$

Constraints (18)–(20) define the range of decision variables used in the proposed problem.

4. Solution Approach

This section presents the proposed algorithm for solving HHCRSP-STW-PM. The greedy randomized adaptive search procedure (GRASP) has been widely applied to combinatorial optimization problems, particularly vehicle routing problem (VRP) variants [57–59] and HHCRSP variants [60,61]. GRASP is a multi-start algorithm consisting of two main phases, a construction phase and a local search phase, which are iteratively applied to explore and refine solutions.

Algorithm 1 outlines the proposed GRASP procedure. Let S^* denote the best solution and S denote the incumbent solution. Both are initialized as empty solutions with positive infinite values for minimization problems (see Line 1). The algorithm iterates for η_{iter} iterations (see Lines 2–6). In each iteration, a solution is first constructed using a randomized greedy-based heuristic, denoted by `constructionHeuristic()` (see Line 3). This solution is then refined through a local search procedure to enhance quality, denoted by `localSearch(S)` (see Line 4). At the end of each iteration, the best solution is updated accordingly (see Lines 5 and 6). The algorithm outputs the best solution S^* after completing all iterations (see Line 7).

The following subsections detail the main components of GRASP. Section 4.1 explains the solution representation for HHCRSP-STW-PM. Section 4.2 details the procedure for updating a solution and evaluating its objective value. Section 4.3 describes the construction heuristic employed in GRASP. Finally, Section 4.4 discusses the local search phase with neighborhood operators to refine solutions.

Algorithm 1 GRASP(η_{iter}) pseudocode.

```

1:  $S, S^* \leftarrow \emptyset, f(S), f(S^*) \leftarrow +\infty$ 
2: while  $\iota < \eta_{iter}$  do
3:    $S \leftarrow \text{constructionHeuristic}()$  ▷ see Section 4.3
4:    $S \leftarrow \text{localSearch}(S)$  ▷ see Section 4.4
5:   if  $f(S) < f(S^*)$  then
6:      $S^* \leftarrow S, f(S^*) \leftarrow f(S)$ 
7: return  $S^*$ 

```

4.1. Solution Representation

A solution of HHCRSP-STW-PM can be represented as a set of η_K 2D arrays, where each array corresponds to a specific period and contains the set of tours scheduled within that period, ensuring that all patient requests are served. Each care crew assigned to a tour is structured as a row that begins and ends at MC (0) while maintaining compatibility between the requested skill service and the assigned care crew (θ_p). Additionally, the problem allows soft time windows, but no waiting time is permitted during tours. Therefore, the start time of each tour (τ_0) must be determined to minimize penalty costs (see Section 4.2). This representation inherently ensures the following: (1) All patient requests are served within the defined planning periods; (2) Skill compatibility (θ_p) is maintained between care crews and required services and (3) Medicine perishability constraints are respected. Figure 2 provides an example based on the solution depicted in Figure 1.

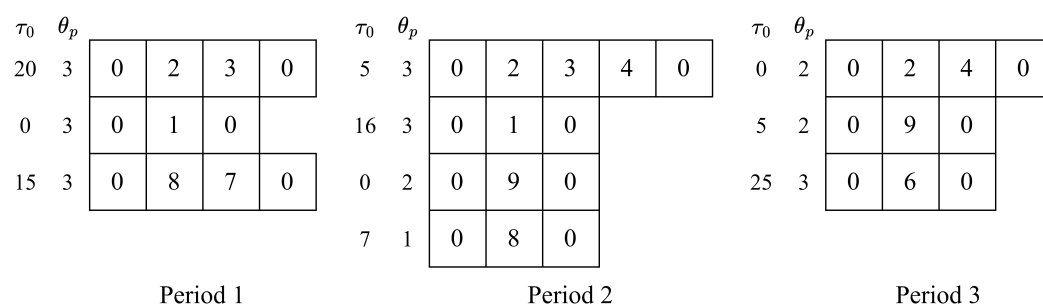


Figure 2. Solution representation for the example in Figure 1.

4.2. Evaluation of the Objective Function

Our approach considers only feasible solutions, where the objective value $f(S)$ of a given solution S is defined as the sum of the total travel cost $f_{travel}(S)$ and penalty cost $f_{pen}(S)$ incurred due to early and late services. Each solution S comprises planning for η_K periods, where each plan consists of a set of tours. A tour (p, k) represents the assigned tour of care crew $p \in P$ during period $k \in K$, which visits a subset of patients $C_{pk} \subseteq C$ in a predefined sequence. The penalty cost $f_{pen}(S)$ depends on the start time of each tour, which can be independently optimized to minimize penalty costs. We note that some notations used in this section are defined in Section 3 for consistency and clarity.

Algorithm 2 computes the objective value $f(S)$ of solution S while simultaneously determining the optimal start time τ_{0pk} for each tour (p, k) , denoted by `evaluateObjective(S)`. Initially, the total travel cost f_{travel} is computed in $\mathcal{O}(1)$ time complexity (see Line 1). The penalty cost $\delta_{pk}(\tau_{0pk})$ for each tour (p, k) is subsequently determined, as it depends on the tour's start time τ_{0pk} (see Lines 3–12). Finally, the objective value is updated and returned (see Lines 13 and 14).

For each tour (p, k) , the algorithm computes the earliest feasible start time $\tau_{0pk}^{\min}$ and the latest feasible start time $\tau_{0pk}^{\max}$, within which no penalty is incurred. Here, τ'_{ipk} denotes the cumulative arrival time at each patient $i \in C_{pk}$ assuming the tour starts at $\tau_{0pk} = 0$ (see

Lines 4 and 5). If $\tau_{0pk}^{\min} \leq \tau_{0pk}^{\max}$, then the penalty-free tour (p, k) exists and the tour's start time is set to $\tau_{0pk}^{\min}$ (see Lines 7 and 8); otherwise, a set of candidate start times $\mathcal{L}$ is generated to identify the start time that minimizes the total penalty $\delta_{pk}(\tau_{0pk})$ (see Lines 10 and 11).

To be specific, the candidate start time is identified by the maximum gaps between the actual arrival of the care-crew and both bounds of the candidate time window. If the arrival is earlier than the time window, the tour is shifted backward but cannot exceed the lower bound of the working hour of the associated care-crew. If the arrival is bounded by the time windows, the care-crew will not modify their tour start time since there were no signs of time window violation. Otherwise, the tour starting time is shifted forward by the exact amount of the gaps but cannot exceed the care-crew's upper working hour. The total penalty cost is then updated accordingly (see Line 12). We note that if a tour (p, k) starts at τ_{0pk} , then the penalty cost $\delta_{pk}(\tau_{0pk})$ is computed as follows.

$$\delta_{pk}(\tau_{0pk}) = \sum_{i \in C_{pk}} \left(\max(0, a(l_{ik} - \tau'_{ipk} - \tau_{0pk}) + \max(0, b(\tau'_{ipk} + s_i + \tau_{0pk} - u_{ik})) \right) \quad \forall p \in P, k \in K \quad (21)$$

Assume that the care crew p works in the shift $[480, 960]$ and is assigned to a tour visiting five patients with time windows $[360, 600]$, $[550, 650]$, $[700, 800]$, $[700, 800]$, and $[850, 1000]$, respectively. The initial arrival times, including the MC departure and return times, are $(480, 545, 625, 670, 760, 795, 850)$, where 480 is the departure time and 850 is the return time. Assume that $s_i = 10$ incurs early penalties of 30 and 55 time units, respectively, so the total penalty time is 85 (assuming $a = b = 1$).

Line 10 then evaluates feasible start-time adjustments for this fixed tour. If the tour is shifted forward by 55 time units, the arrival times become $(535, 600, 680, 725, 815, 850, 905)$. In this schedule, the second and fourth patients violate their time windows by 40 and 25 time units, respectively, resulting in a total penalty time of 65. A backward re-adjustment is then evaluated. When the arrival times are shifted to $(495, 560, 640, 685, 775, 810, 865)$, the third and fifth patients are served 15 and 40 time units earlier, respectively. The total penalty time is, therefore, 55, which is 30 time units less than the initial schedule. This is the optimal assignment because the next shift will result in a 65-time-unit penalty.

Algorithm 2 evaluateObjective(S).

```

1:  $f_{travel}(S) \leftarrow$  Updated in  $\mathcal{O}(1)$  time complexity
2:  $f_{pen}(S) \leftarrow 0$ 
3: for each tour  $(p, k) \in S$  do
4:    $\tau_{0pk}^{\min} \leftarrow \max_{i \in C_{pk}} (l_{ik} - \tau'_{ipk})$ 
5:    $\tau_{0pk}^{\max} \leftarrow \min_{i \in C_{pk}} (u_{ik} - \tau'_{ipk})$ 
6:   if  $\tau_{0pk}^{\min} \leq \tau_{0pk}^{\max}$  then
7:      $\tau_{0pk} \leftarrow \tau_{0pk}^{\min}$ 
8:      $\delta_{pk}(\tau_{0pk}) \leftarrow 0$ 
9:   else
10:     $\mathcal{L} \leftarrow \{\max(0, l_{ik} - \tau'_{ipk}), \max(0, \tau'_{ipk} - u_{ik}) | i \in C_{pk}\}$   $\triangleright$  Candidate start times
11:     $\tau_{0pk} \leftarrow \operatorname{argmin}_{\sigma \in \mathcal{L}} \delta_{pk}(\sigma)$ 
12:     $f_{pen}(S) \leftarrow f_{pen}(S) + \delta_{pk}(\tau_{0pk})$   $\triangleright \delta_{pk}(\tau_{0pk})$  is computed by Equation (21)
13:  $f(S) \leftarrow f_{travel}(S) + f_{pen}(S)$ 
14: return  $f(S)$ 

```

4.3. Construction Phase

A modified greedy-based insertion heuristic with randomness factors is proposed as a construction heuristic, denoted by `constructionHeuristic()`. This heuristic generates

a feasible solution while ensuring both solution quality and the diversity of solutions in GRASP iterations.

Algorithm 3 presents the `constructionHeuristic()` procedure, which constructs an initial feasible solution. The algorithm begins by initializing an empty solution S (see Line 1) and iteratively builds the solution for each planning period $k \in K$ (see Lines 2–14). For each planning period $k \in K$, a partial solution for that period, denoted as S_k , includes a set of tours, initialized as an empty set (see Line 3). Let $\mathcal{C}_{\text{unassigned}}$ denote a set of unassigned patients, which is initialized as the set of all patients requiring service in period k , represented as C_k (see Line 4). An iterative insertion procedure continues to insert all patients into S_k , ensuring feasibility constraints (see Lines 5–13). The completed schedule S_k is then added into the overall solution S (see Line 14). The output is a feasible solution S (see Line 15).

During each insertion process, let $\mathcal{L}^{\text{potential}}$ denote the set of potential insertions, which is initialized as an empty set (see Line 6). This set is populated by evaluating all feasible insertions for each unassigned patient (see Lines 7–9). Each potential insertion is represented by a tuple $\{i, \text{tour}_i, \text{pos}_i, \text{score}_i\}$, where i denotes the considered patient, tour_i specifies the tour in which the patient is inserted, pos_i defines the position within the inserted tour, and score_i evaluates the quality of the insertion. These values are evaluated by using the `greedyEvaluate()` function (see Line 8). $\mathcal{L}^{\text{potential}}$ is then updated (see Line 9). As $\mathcal{L}^{\text{potential}}$ is constructed, it is sorted by score_i in ascending order for selection (see Line 10). To introduce randomness into the construction heuristic, the next insertion $\{i^*, \text{tour}_{i^*}, \text{pos}_{i^*}\}$ is chosen as the $\lceil \xi \times p_{\text{best}} \rceil$ -th candidate in $\mathcal{L}^{\text{potential}}$, where $\xi \sim U(0, 1)$ is a uniformly distributed random number, and p_{best} represents the randomness level, set to 5 (see Line 11). The selected patient i^* is then inserted into S_k at the corresponding tour and position (see Line 12).

Algorithm 3 `constructionHeuristic()`.

```

1:  $S \leftarrow \emptyset$ 
2: for each period  $k \in K$  do
3:    $S_k \leftarrow \emptyset$ 
4:    $\mathcal{C}_{\text{unassigned}} \leftarrow C_k$ 
5:   while  $\mathcal{C}_{\text{unassigned}} \neq \emptyset$  do
6:      $\mathcal{L}^{\text{potential}} \leftarrow \emptyset$ 
7:     for  $i \in \mathcal{C}_{\text{unassigned}}$  do
8:        $i, \text{tour}_i, \text{pos}_i, \text{score}_i \leftarrow \text{greedyEvaluate}(S_k, i)$ 
9:        $\mathcal{L}^{\text{potential}} \leftarrow \mathcal{L}^{\text{potential}} \cup \{(i, \text{tour}_i, \text{pos}_i, \text{score}_i)\}$ 
10:     $\mathcal{L}^{\text{potential}} \leftarrow \text{Sort the list by ascending } \text{score}_i$ 
11:     $i^*, \text{tour}_{i^*}, \text{pos}_{i^*} \leftarrow \text{Select the } \lceil \xi \times p_{\text{best}} \rceil\text{-th insertion in } \mathcal{L}^{\text{potential}}$ 
12:    Update  $S_k$  by inserting  $i^*$  into tour  $\text{tour}_{i^*}$  at position  $\text{pos}_{i^*}$ 
13:     $\mathcal{C}_{\text{unassigned}} \leftarrow \mathcal{C}_{\text{unassigned}} \setminus \{i^*\}$ 
14:    $S \leftarrow S \cup S_k$ 
15: return  $S$ 

```

In `greedyEvaluate( $S_k, i$ )` we assess potential insertion positions for patient i into the current solution S_k at period k using a greedy-based function with randomness. The objective is to determine the best insertion position that minimizes the associated score while maintaining feasibility. Each candidate insertion is represented as $(\text{tour}'_i, \text{pos}'_i)$, where tour'_i denotes the selected tour within S_k in which patient i is being considered for insertion, and pos'_i represents the specific position within the tour where the insertion is evaluated. For each candidate position $(\text{tour}'_i, \text{pos}'_i)$, a corresponding score is computed as follows.

$$score'_i(tour'_i, pos'_i) = w_1 \frac{1}{\Gamma_i} + w_2 \frac{1}{\beta_i} + w_3 \delta_{cost} + w_4 \delta_{penalty} \quad (22)$$

Here, δ_{cost} denotes the incremental travel cost incurred by inserting patient i at position $(tour'_i, pos'_i)$, while $\delta_{penalty}$ represents the penalty cost associated with the insertion. Moreover, w_1, w_2, w_3 , and w_4 represent weight parameters corresponding to patient prioritization based on medicine shelf life, required skill level, travel cost, and time penalties, respectively. Additionally, each weight is perturbed to introduce randomness: $w_c = w_c^0(1 + \mathcal{R})$ for each $c = \{1, \dots, 4\}$, where $\mathcal{R} \sim U(-1, 1)$, and w_c^0 represents the initial value of the associated weight.

4.4. Local Search Phase

For the local search phase, we adopt the variable neighborhood descent (VND) framework [62]. Based on the concept of classical neighborhood operators [63,64], with a modification to address specific problem characteristics, a set of neighborhood operators (denoted by $\mathcal{O}$) is proposed to improve solutions, which are described as follows.

- $\mathcal{O}_1(S)$: Shift operator removes a patient from its current position and reinserts it at a different location within the same tour.
- $\mathcal{O}_2(S)$: Swap operator swaps the positions of two different patients within the same tour to generate a new solution.
- $\mathcal{O}_3(S)$: 2-Opt operator selects a segment within a tour and reverses its sequence to obtain a new solution. A segment is the path between two patients within a tour.
- $\mathcal{O}_4(S)$: Shift-Inter operator removes a patient from its current location and reinserts it into a different position in another tour. Additionally, if the solution contains empty tours, this operator creates a new tour by assigning the patient to it.
- $\mathcal{O}_5(S)$: Swap-Inter operator exchanges the positions of two patients from different tours to generate a new neighboring solution.
- $\mathcal{O}_6(S)$: 2-Opt* operator selects two tours and divides each into two segments. The first segment from the first tour is combined with the second segment from the second tour, and vice versa, creating two new tours.
- $\mathcal{O}_7(S)$: OrOpt operator removes a segment from a tour and reinserts it at a different position within the same tour to generate a new solution.
- $\mathcal{O}_8(S)$: DestroyTour operator removes an entire tour from the solution and reinserts the removed patients into the remaining tours. The insertion positions are determined based on the minimal increase in the objective value.

The search process ensures feasibility by strictly adhering to key constraints including the following: (1) The compatibility of skill levels must be ensured so that assigned care crews possess the required expertise for each patient; (2) Services must be completed within the medicine's shelf life to maintain treatment effectiveness and (3) All patient requests associated with predefined periods are fully served within care crews' working hours.

Algorithm 4 presents the local search procedure, denoted by `localSearch(S)`, where S represents the given solution to be improved. Let S' be the incumbent solution. We also denote h as the selected operator index, initialized to 1 (see Line 1). Each operator in $\mathcal{O}$ is sequentially applied until no further improvement is found across all operators (see Lines 2–8). For implementing each operator, the procedure follows a first-improvement strategy, terminating the search upon finding a better solution (see Line 3). We note that `evaluateObjective(S)` is used to determine the solution quality during the search. If an improved solution is found, then the best solution is updated, and the search restarts with the first operator in the next iteration (see Lines 4–6); otherwise, the subsequent operator is

implemented in the following iteration (see Line 8). The output is an improved solution (see Line 9).

Algorithm 4 localSearch(S) pseudocode.

```

1:  $h \leftarrow 1$ 
2: while  $h \leq |\mathcal{O}|$  do
3:    $S' \leftarrow \mathcal{O}_h(S)$ 
4:   if  $f(S') < f(S)$  then
5:      $S \leftarrow S', f(S) \leftarrow f(S')$ 
6:      $h \leftarrow 1$ 
7:   else
8:      $h \leftarrow h + 1$ 
9: return  $S$ 

```

5. Computational Results

This section presents numerical experiments to analyze our proposed problem and to evaluate the performance of GRASP. Section 5.1 describes the HHCRSP-STW-PM benchmark instances. Section 5.2 reports the results of HHCRSP-STW-PM instances obtained using the mathematical model and GRASP. Section 5.3 provides a sensitivity analysis of key factors and discusses managerial insights. All experiments are conducted on a computer with an Intel Core i7-10700 CPU (2.90 GHz) and 32 GB of RAM. The MILP model is solved using the GUROBI solver, while GRASP is implemented in Python 3.10.11.

5.1. Data Description

We generated the test HHCRSP-STW-PM instances based on benchmark HHCRSP instances, which reflect real-life characteristics observed by the Austrian Red Cross (ARC) [43]. The dataset includes 26 instances with 6–12 care crews and 20–60 patients. Additionally, to evaluate the MILP model, we introduce 12 new smaller instances with 3–9 care crews and 6–15 patients. Each instance is named by using the format x_y_z , where x represents the number of care crews, y denotes the number of patients, and z is the instance index. All instances follow a seven-period (i.e., seven-day) planning horizon. To address new components, we introduce additional information as follows.

- Care crews are classified into three skill levels, ranging from 1 to 3. For all instances, we assume that the number of care crews is equal.
- Patients are grouped into three types based on required services, with each assigned a specific set of medicines with different shelf lives: long-term (equal to care crew working hours), medium-term (80% of working hours), and short-term (40% of working hours).
- The unit operation cost is set to $\gamma = 1$, while penalty costs are fixed at $a = b = 2$. These parameters are further examined in the sensitivity analysis.

5.2. Results on HHCRSP-STW-PM Instances

This section presents detailed results on HHCRSP-STW-PM instances, comparing the performance of GRASP with that of the GUROBI solver. Regarding computational time, the GUROBI solver is given a time limit of 2 h, while the number of iterations η_{iter} , in GRASP is set to 5000. The algorithm is executed 10 times per instance to obtain the best solution (f_a) and the average solution (f_b). We also compute Δf_a and Δf_b , which correspondingly represent the gaps between the best and average solutions obtained by GRASP and the solutions obtained by GUROBI. These values are computed by $\Delta f_a[\%] = \frac{f_a - f^*}{f^*}$ and $\Delta f_b[\%] = \frac{f_b - f^*}{f^*}$, where f^* denotes the solution obtained by GUROBI. Computational time (CPU) is recorded in seconds.

Table 3 presents the detailed results of small-sized instances obtained by GUROBI and GRASP. GUROBI successfully finds the optimal solutions for all instances. On the other hand, GRASP achieves optimality across all runs while significantly reducing computational time and requiring only 0.11 s on average compared to 5.08 s with GUROBI.

Table 3. Comparison of the results of the small instances between GUROBI solver and GRASP.

Instance	η_P	η_C	GUROBI		GRASP		GAP (Δf [%])			
			f	CPU (s)	f_a	f_b	CPU(s)	Δf_{b-a}	Δf_a	Δf_b
3_6_1	3	6	1372	0.50	1372	1372	0.10	0.00	0.00	0.00
3_8_1	3	8	3515	1.66	3515	3515	0.11	0.00	0.00	0.00
3_9_1	3	9	2128	3.00	2128	2128	0.11	0.00	0.00	0.00
6_5_1	6	5	839	0.34	839	839	0.10	0.00	0.00	0.00
6_5_2	6	5	632	0.39	632	632	0.10	0.00	0.00	0.00
6_8_1	6	8	877	4.31	877	877	0.11	0.00	0.00	0.00
6_10_1	6	10	1138	4.84	1138	1138	0.12	0.00	0.00	0.00
6_10_2	6	10	1173	5.70	1173	1173	0.13	0.00	0.00	0.00
6_10_3	6	10	1458	4.03	1458	1458	0.12	0.00	0.00	0.00
6_15_1	6	15	2755	23.78	2755	2755	0.15	0.00	0.00	0.00
9_8_1	9	8	644	0.58	644	644	0.10	0.00	0.00	0.00
9_9_1	9	9	1300	11.84	1300	1300	0.12	0.00	0.00	0.00
Average				5.08			0.11	0.00	0.00	0.00

Table 4 presents the detailed results for large-sized instances obtained using both GUROBI and GRASP. While GUROBI can solve only a limited number of instances (specifically, those with up to 6 care crews and 30 patients), GRASP consistently provides feasible solutions for all instances in every run. The robustness of GRASP is further demonstrated by the small gap between the average and best solutions, computed as $\Delta f_{b-a} = \frac{f_b - f_a}{f_b}$, which remains at just 2.85%. To sum up, GRASP is an effective approach for solving HHCRSP-STW-PM instances within a reasonable computational time, averaging 827.90 s. These results mean that GRASP can be positively implemented to conduct further analysis in subsequent sections.

Table 4. Comparison of the results of the large instances between GUROBI solver and GRASP.

Instance	η_P	η_C	GUROBI		GRASP		GAP (Δf [%])			
			f	CPU (s)	f_a	f_b	CPU(s)	Δf_{b-a}	Δf_a	Δf_b
6_20_1	6	20	3126	79.781	3126	3126	0.30	0.00	0.00	0.00
6_30_1	6	30	3635	3148	3635	3748	10.08	3.10	0.00	3.00
6_30_2	6	30	2605	344.92	2605	2631	1.65	1.00	0.00	0.99
6_30_3	6	30	-	7200	5214	5308	190.37	1.80	-	-
6_30_4	6	30	-	7200	5040	5166	203.55	2.50	-	-
6_30_5	6	30	-	7200	4190	4261	165.11	1.70	-	-
6_30_6	6	30	-	7200	4177	4265	216.84	2.10	-	-
6_30_7	6	30	-	7200	5158	5261	218.77	2.00	-	-
6_30_8	6	30	4254	6754	4254	4442	19.19	4.43	0.00	4.24
6_30_9	6	30	-	7200	5736	5839	189.15	1.80	-	-
6_30_10	6	30	4146	2638	4146	4262	15.59	2.80	0.00	2.73
9_35_5	9	35	-	7200	5584	5696	486.67	2.00	-	-
9_40_6	9	40	-	7200	4358	4441	870.26	1.90	-	-
9_45_1	9	45	-	7200	6369	6471	1,196	1.60	-	-

Table 4. Cont.

Instance	η_P	η_C	GUROBI		GRASP			GAP (Δf [%])		
			f	CPU (s)	f_a	f_b	CPU(s)	Δf_{b-a}	Δf_a	Δf_b
9_45_2	9	45	-	7200	18,533	19,200	1019	3.60	-	-
9_45_3	9	45	-	7200	4888	4986	909	2.00	-	-
9_45_4	9	45	-	7200	4909	5120	1151	4.30	-	-
9_45_5	9	45	-	7200	16,073	16,668	1308	3.70	-	-
9_45_6	9	45	-	7200	8548	8933	1364	4.50	-	-
9_45_7	9	45	-	7200	13,312	13,658	1048	2.60	-	-
9_45_8	9	45	-	7200	19,654	20,381	928	3.70	-	-
9_45_9	9	45	-	7200	18,594	19,170	1047	3.10	-	-
9_45_10	9	45	-	7200	15,052	15,714	1249	4.40	-	-
9_45_11	9	45	-	7200	17,424	18,051	1150	3.60	-	-
12_50_1	12	50	-	7200	10,634	11,123	3002	4.60	-	-
12_60_1	12	60	-	7200	15,439	16,257	3565	5.30	-	-
Average				6314			827.90	2.85	0.00	2.19

5.3. Sensitivity Analysis

To further evaluate the effects of perishable medicines, care crew resources, and unit cost weights, we conduct additional experiments using a randomly selected HHCRSP-STW-PM instance (i.e., instance 6_30_3 with 6 nurses and 30 patients). The best results are evaluated over 10 runs, with parameter variations designed to assess their impact on operational and penalty costs as follows.

- The shelf life of medicine for each patient $i \in C$ is reduced to Γ_i^0 , $0.9\Gamma_i^0$, $0.8\Gamma_i^0$, and $0.7\Gamma_i^0$, where Γ_i^0 represents the initial values used in Section 5.2.
- Care crew availability is set to $\eta_P \in \{3, 6, 9\}$ with an equal distribution across skill levels. For instance, $\eta_P = 6$ means that there are two care crews per skill level.
- Cost parameters include variations in unit travel cost (i.e., $\gamma \in \{1, 2, 3\}$) and unit penalty costs for early and late services (i.e., $a, b \in \{1, 2, 3\}$).

Table 5 presents the detailed results obtained by GRASP under various parameter settings. The table reports travel cost f_{travel} , total penalty cost f_{pen} , and total cost f for each configuration, which is defined by $(\eta_P, \gamma, a, b, \Gamma_i)$. Based on these results, the key observations and highlights are summarized as follows.

- Figure 3 illustrates that as the medicine shelf life decreases, all cost components generally increase, with total costs rising significantly when care crew resources are limited (i.e., $\eta_P = 3$ and 6). Adding more care crews does not always reduce travel costs; however, it can reduce penalty costs by improving routing and scheduling flexibility. Notably, the setting with $\eta_P = 9$ shows that a moderate increase in travel cost may still be acceptable when it leads to a larger reduction in penalty cost.
- Figure 4 shows that penalty costs (see red lines) dominate when fewer care crews are available (i.e., $\eta_P = 3$ and 6) due to frequent early or late visits. However, as the number of care crews increases (i.e., $\eta_P = 9$), the trade-off between travel costs (see gray lines) and penalties (see red lines) becomes more evident. Interestingly, travel costs remain nearly unchanged despite the increase in care crew resources, suggesting that penalty reduction is the primary benefit of expanding workforce availability.

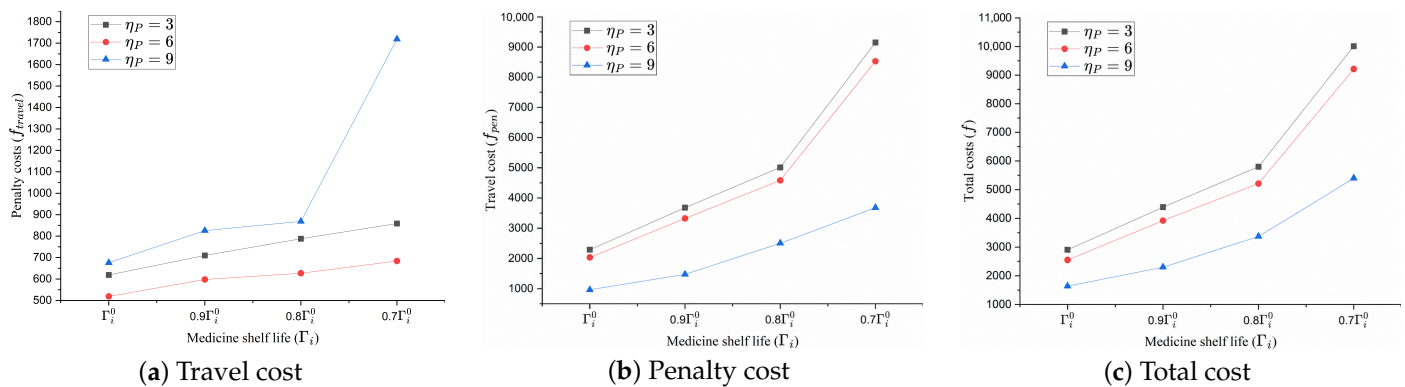


Figure 3. Effects of medicine shelf life and care crew resources on cost components with $\gamma = a = b = 1$.

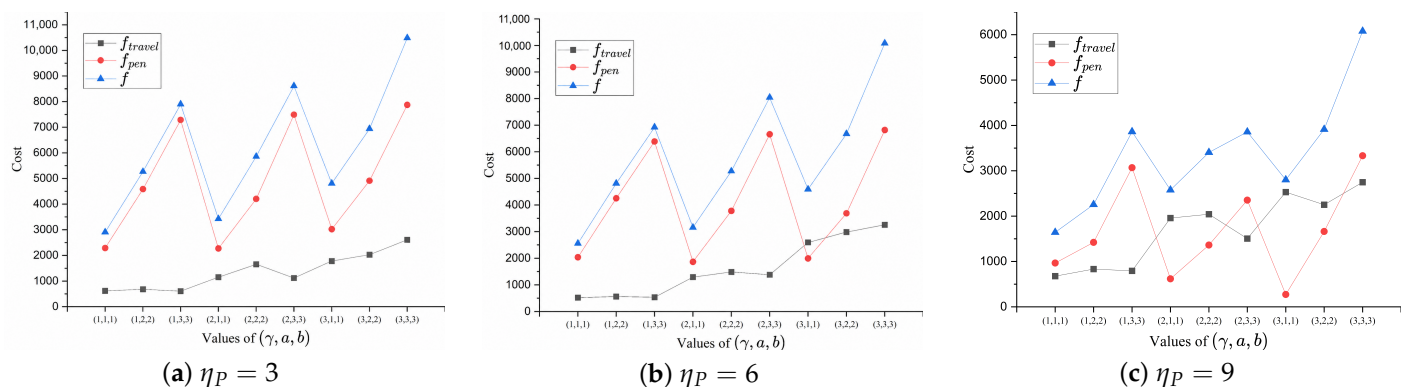


Figure 4. Effects of cost component weights under varying care crew resource levels with $\Gamma_i = \Gamma_i^0$.

Based on these findings, several recommendations can be suggested for HHC managers. First, patients requiring short shelf-life medicines should be scheduled with higher priority and, when possible, placed near the beginning of a care crew's tour to reduce the risk of medicine expiration and high penalty costs. Second, care crew availability should be adjusted according to the share of penalty cost in the total cost. When penalty cost dominates, adding temporary care crews or splitting long tours may be cost-effective, even if travel cost slightly increases. Third, hospitals should compare the reduction in penalty cost with the additional staffing cost before increasing the number of care crews.

Table 5. Detailed results of HHCRSP-STW-PM under varying parameters.

η_P	γ	$a = b$	$\Gamma_i = \Gamma_i^0$			$\Gamma_i = 0.9\Gamma_i^0$			$\Gamma_i = 0.8\Gamma_i^0$			$\Gamma_i = 0.7\Gamma_i^0$		
			f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f
3	1	1	619	2291	2910	710	3682	4392	788	5013	5801	859	9153	10,012
3	1	2	684	4587	5271	751	6638	7389	785	10,505	11,290	821	16,953	17,774
3	1	3	609	7291	7900	662	10,475	11,137	833	15,486	16,319	864	26,030	26,894
3	2	1	1154	2273	3427	1225	3896	5121	1252	6284	7536	1401	11,591	12,992
3	2	2	1655	4204	5859	1757	7772	9529	1793	14,382	16,175	2100	22,159	24,259
3	2	3	1121	7490	8611	1751	12,796	14,547	1764	22,185	23,949	1819	33,436	35,255
3	3	1	1784	3027	4811	2237	6741	8978	2784	8842	11,626	3005	12,584	15,589
3	3	2	2029	4914	6943	2329	9699	12,028	2530	15,649	18,179	2979	22,800	25,779
3	3	3	2610	7875	10,485	2994	17,507	20,501	3350	24,510	27,860	3542	38,377	41,919
6	1	1	519	2038	2557	598	3327	3925	627	4585	5212	684	8531	9215
6	1	2	562	4253	4815	707	6246	6953	762	8730	9492	795	15,330	16,125
6	1	3	534	6392	6926	628	9266	9894	663	12,895	13,558	684	22,188	22,872
6	2	1	1292	1870	3162	1393	3401	4794	1419	5672	7091	1548	10,099	11,647
6	2	2	1490	3785	5275	1565	6922	8487	1895	11,996	13,891	2038	19,193	21,231
6	2	3	1382	6661	8043	1543	12,106	13,649	1777	18,274	20,051	2286	29,890	32,176

Table 5. Cont.

η_P	γ	$a = b$	$\Gamma_i = \Gamma_i^0$			$\Gamma_i = 0.9\Gamma_i^0$			$\Gamma_i = 0.8\Gamma_i^0$			$\Gamma_i = 0.7\Gamma_i^0$		
			f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f	f_{travel}	f_{pen}	f
6	3	1	2597	1996	4593	2789	5492	8281	2868	7846	10,714	2956	11,227	14,183
6	3	2	2985	3691	6676	3267	8255	11,522	3297	13,740	17,037	3512	19,297	22,809
6	3	3	3260	6822	10,082	3549	15,418	18,967	3874	21,018	24,892	4095	35,435	39,530
9	1	1	676	966	1642	826	1478	2304	869	2506	3375	1719	3681	5400
9	1	2	833	1422	2255	895	3083	3978	1182	3795	4977	1815	4364	6179
9	1	3	793	3069	3862	1048	3646	4694	1304	7009	8313	1567	8568	10,135
9	2	1	1958	618	2576	2652	786	3438	2734	2114	4848	3447	3147	6594
9	2	2	2042	1362	3404	2145	3652	5797	2316	6140	8456	2575	7177	9752
9	2	3	1504	2353	3857	2028	3852	5880	2379	7116	9495	2483	11,233	13,716
9	3	1	2529	272	2801	2977	799	3776	3451	1767	5218	3612	6153	9765
9	3	2	2251	1662	3913	2510	1905	4415	2611	6277	8888	3451	10,543	13,994
9	3	3	2747	3331	6078	2895	5065	7960	3001	9924	12,925	3188	15,091	18,279

6. Conclusions

This research addresses the home health care routing and scheduling problem with soft time windows and perishable medicines (HHCRSP-STW-PM), focusing on the impact of medicine shelf life on service quality. The problem framework allows for a more flexible system that permits early and late services with additional penalty costs, thereby balancing operational expense minimization. The objective function incorporates weighted travel and penalty costs, accounting for different care crew types with varying skill levels to accommodate diverse service requirements.

We develop a mixed-integer linear programming (MILP) model and propose an efficient greedy randomized adaptive search procedure (GRASP) algorithm. While the MILP model can obtain optimal solutions only for small instances with the GUROBI solver, the proposed GRASP effectively provides feasible solutions for all instances within reasonable computational times. The computational results show that GRASP can generate high-quality solutions. The sensitivity analysis further indicates that medicine shelf life, care crew availability, and cost-weight settings strongly affect routing and scheduling decisions.

The results suggest several managerial implications. Patients requiring short shelf-life medicines should be prioritized and, when possible, scheduled earlier in a care crew's tour. Soft time windows can provide scheduling flexibility, but medicine-validity constraints must remain strictly satisfied. When penalty costs account for a large share of total costs, managers may consider adding temporary care crews, splitting long tours, or reassigning patients among crews during peak periods. These decisions should be evaluated by comparing the reduction in penalty cost with the additional staffing and travel costs.

Several future research directions can be considered. Future studies may extend the model by considering uncertain or time-dependent travel times, urgent requests, cancellations, and stochastic patient demand. More advanced perishability models can also be developed to represent dynamic medicine validity under different storage or routing conditions. In addition, inter-period constraints such as continuity of care and workload balance may be incorporated. Finally, testing the proposed model with real healthcare datasets and comparing our proposed algorithm with other well-known metaheuristics would further evaluate its practical effectiveness.

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References

1. Cissé, M.; Yalçındağ, S.; Kergosien, Y.; Şahin, E.; Lenté, C.; Matta, A. OR problems related to Home Health Care: A review of relevant routing and scheduling problems. *Oper. Res. Health Care* **2017**, *13–14*, 1–22.
2. Mordor Intelligence. Home Healthcare Market Size & Share Analysis—Growth Trends and Forecast (2026–2031). Available online: <https://www.mordorintelligence.com/industry-reports/home-healthcare-market> (accessed on 14 February 2025).
3. Di Mascolo, M.; Martinez, C.; Espinouse, M.L. Routing and scheduling in Home Health Care: A literature survey and bibliometric analysis. *Comput. Ind. Eng.* **2021**, *158*, 107255. <https://doi.org/10.1016/j.cie.2021.107255>.
4. Rastegar, J.; Brown, V.T.; John, I.; Dixon, S.W.; Rodman, E.; Ellis, J.J.; Poonawalla, I.B. Home versus outpatient hospital intravenous immunoglobulin infusion and health care resource utilization. *J. Am. Pharm. Assoc.* **2023**, *63*, 1566–1573.
5. Serramontmany, E.; Muñoz, M.; Fernández-Polo, A.; Morillo, M.; Gómez-Ganda, L.; Cañete-Ramírez, C.; Ariceta, G. Home albumin infusion therapy, another alternative treatment in patients with congenital nephrotic syndrome of the Finnish type. *Front. Pediatr.* **2021**, *8*, 614535.
6. Carbone, F.; Djamshidian, A.; Seppi, K.; Poewe, W. Apomorphine for Parkinson’s disease: Efficacy and safety of current and new formulations. *CNS Drugs* **2019**, *33*, 905–918.
7. Arda, Y.; Cattaruzza, D.; François, V.; Ogier, M. Home chemotherapy delivery: An integrated production scheduling and multi-trip vehicle routing problem. *Eur. J. Oper. Res.* **2024**, *317*, 468–486.
8. Coelho, L.C.; Mancini, S. The collect-and-process vehicle routing problem with completion time minimization: An application in home healthcare. *Eur. J. Oper. Res.* **2026**, In Press. <https://doi.org/10.1016/j.ejor.2026.05.034>.
9. Fernando, V.; Ozlen, M.; Taheri, S. A single nurse routing and scheduling problem for home-based chemotherapy and infusion services. *Eur. J. Oper. Res.* **2026**, 328. <https://doi.org/10.1016/j.ejor.2025.07.038>.
10. Guo, H.; Gao, L.; Shi, Y.; Wu, Y.; Wang, L.; Zhang, W. Optimization for vaccination demand allocation and distribution routes in pandemics based on a hierarchy decision model. *Comput. Ind. Eng.* **2023**, *184*, 109568.
11. Ghasemi, P.; Goodarzian, F.; Abraham, A.; Khanchehazarrin, S. A possibilistic-robust-fuzzy programming model for designing a game theory based blood supply chain network. *Appl. Math. Model.* **2022**, *112*, 282–303.
12. Moshtaghi, M.S.; Zhou, Y.; Verma, M. Coordinating a bi-level blood supply chain with interactions between supply-side and demand-side operational decisions. *Int. Trans. Oper. Res.* **2024**, *33*, 1971–2015.
13. Bazirha, M.; Kadrani, A.; Benmansour, R. Pareto and decomposition based approaches for the multi-objective home health care routing and scheduling problem with lunch breaks. *Eng. Appl. Artif. Intell.* **2024**, *128*, 107502.
14. Yazır, O.A.; Koç, Ç.; Yücel, E. The multi-period home healthcare routing and scheduling problem with electric vehicles. *OR Spectr.* **2023**, *45*, 853–901.
15. Nasir, J.A.; Kuo, Y.H. Stochastic home care transportation with dynamically prioritized patients: An integrated facility location, fleet sizing, and routing approach. *Transp. Res. Part B Methodol.* **2024**, *184*, 102949.
16. Fikar, C.; Hirsch, P. Home health care routing and scheduling: A review. *Comput. Oper. Res.* **2017**, *77*, 86–95.
17. Oladzad-Abbasabady, N.; Tavakkoli-Moghaddam, R.; Mohammadi, M.; Vahedi-Nouri, B. A bi-objective home care routing and scheduling problem considering patient preference and soft temporal dependency constraints. *Eng. Appl. Artif. Intell.* **2023**, *119*, 105829. <https://doi.org/10.1016/j.engappai.2023.105829>.
18. Li, Y.; Xiang, T.; Szeto, W.Y. Home health care routing and scheduling problem with the consideration of outpatient services. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *152*, 102420.
19. Erdem, M.; Koç, Ç.; Yücel, E. The electric home health care routing and scheduling problem with time windows and fast chargers. *Comput. Ind. Eng.* **2022**, *172*, 108580.

20. Zhao, J.; Wang, T.; Monteiro, T. A Bi-Objective Home Health Care Routing and Scheduling Problem under Uncertainty. *Int. J. Environ. Res. Public Health* **2024**, *21*, 377.
21. Varas, M.; Baesler, F.; Basso, F.; Contreras, J.P.; Pezoa, R.; Rojas-Goldsack, M.F.; Ronco, R. A home hospitalization assignment and routing problem with multiple time windows, mandatory returns and perishable biological samples: A Chilean case study. *Comput. Ind. Eng.* **2024**, *189*, 109951.
22. Begur, S.V.; Miller, D.M.; Weaver, J.R. An integrated spatial DSS for scheduling and routing home-health-care nurses. *Interfaces* **1997**, *27*, 35–48.
23. Yuan, B.; Liu, R.; Jiang, Z. A branch-and-price algorithm for the home health care scheduling and routing problem with stochastic service times and skill requirements. *Int. J. Prod. Res.* **2015**, *53*, 7450–7464.
24. Braekers, K.; Hartl, R.F.; Parragh, S.N.; Tricoire, F. A bi-objective home care scheduling problem: Analyzing the trade-off between costs and client inconvenience. *Eur. J. Oper. Res.* **2016**, *248*, 428–443. <https://doi.org/10.1016/j.ejor.2015.07.028>.
25. Delaet, A.; Ramaekers, K.; Hirsch, P.; Molenbruch, Y.; Braekers, K. A matheuristic for integrated medium-term home healthcare planning. *Eur. J. Oper. Res.* **2024**, *319*, 543–556.
26. Tanoumand, N.; Ünlüyurt, T. An exact algorithm for the resource constrained home health care vehicle routing problem. *Ann. Oper. Res.* **2021**, *304*, 397–425.
27. Pahlevani, D.; Abbasi, B.; Hearne, J.W.; Eberhard, A. A cluster-based algorithm for home health care planning: A case study in Australia. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *166*, 102878.
28. Decerle, J.; Grunder, O.; El Hassani, A.H.; Barakat, O. A hybrid memetic-ant colony optimization algorithm for the home health care problem with time window, synchronization and working time balancing. *Swarm Evol. Comput.* **2019**, *46*, 171–183.
29. Grenouilleau, F.; Lahrichi, N.; Rousseau, L.M. New decomposition methods for home care scheduling with predefined visits. *Comput. Oper. Res.* **2020**, *115*, 104855.
30. Zhou, Y.; Pan, Z.; Zhao, Y.; Li, Z. Optimizing multi-period multi-mode multi-time window home health care scheduling with an improved tabu search algorithm. *Swarm Evol. Comput.* **2026**, *100*, 102263.
31. Xiang, T.; Li, Y.; Szeto, W.Y. The daily routing and scheduling problem of home health care: Based on costs and participants' preference satisfaction. *Int. Trans. Oper. Res.* **2023**, *30*, 39–69.
32. Lin, M.; Chin, K.S.; Wang, X.; Tsui, K.L. The therapist assignment problem in home healthcare structures. *Expert Syst. Appl.* **2016**, *62*, 44–62. <https://doi.org/10.1016/j.eswa.2016.06.010>.
33. Gobbi, A.; Manerba, D.; Mansini, R.; Zanotti, R. Hybridizing adaptive large neighborhood search with kernel search: A new solution approach for the nurse routing problem with incompatible services and minimum demand. *Int. Trans. Oper. Res.* **2023**, *30*, 8–38.
34. Mosquera, F.; Smet, P.; Berghe, G.V. Flexible home care scheduling. *Omega* **2019**, *83*, 80–95.
35. Kummer, A.F.; de Araújo, O.C.; Buriol, L.S.; Resende, M.G. A biased random-key genetic algorithm for the home health care problem. *Int. Trans. Oper. Res.* **2024**, *31*, 1859–1889.
36. Liu, W.; Dridi, M.; Fei, H.; El Hassani, A.H.; Shi, Y. A Q-learning-based approach for solving a fuzzy home health care routing and scheduling problem with physical load of caregivers. *Appl. Soft Comput.* **2026**, *192*, 114779.
37. Ceschia, S.; Di Gaspero, L.; Rosati, R.M.; Schaerf, A. Multi-neighborhood simulated annealing for the home healthcare routing and scheduling problem. *Int. Trans. Oper. Res.* **2024**, *33*, 38–67.
38. Mankowska, D.S.; Meisel, F.; Bierwirth, C. The home health care routing and scheduling problem with interdependent services. *Health Care Manag. Sci.* **2014**, *17*, 15–30.
39. Duque, P.M.; Castro, M.; Sörensen, K.; Goos, P. Home care service planning. The case of Landelijke Thuiszorg. *Eur. J. Oper. Res.* **2015**, *243*, 292–301.
40. Bard, J.F.; Shao, Y.; Jarrah, A.I. A sequential GRASP for the therapist routing and scheduling problem. *J. Sched.* **2014**, *17*, 109–133.
41. Rest, K.D.; Hirsch, P. Daily scheduling of home health care services using time-dependent public transport. *Flex. Serv. Manuf. J.* **2016**, *28*, 495–525.
42. Bertels, S.; Fahle, T. A hybrid setup for a hybrid scenario: Combining heuristics for the home health care problem. *Comput. Oper. Res.* **2006**, *33*, 2866–2890.
43. Trautsamwieser, A.; Hirsch, P. A Branch-Price-and-Cut approach for solving the medium-term home health care planning problem. *Networks* **2014**, *64*, 143–159.
44. Cappanera, P.; Scutellà, M.G. Joint assignment, scheduling, and routing models to home care optimization: A pattern-based approach. *Transp. Sci.* **2015**, *49*, 830–852.
45. Mohammadi-Kordkheili, B.; Sahraeian, R.; Costa, Y. Improved benders decomposition for home healthcare vehicle and drone routing problem in two-echelon supply chains. *Comput. Oper. Res.* **2025**, *186*, 107306.
46. Lu, Y.; Yang, J.; Yang, C.; Zheng, R. Multi-objective home healthcare vehicle routing problem with drone-caregiver cooperation mode. *Comput. Ind. Eng.* **2025**, *213*, 111714.

47. Nasirian, A.; Zhang, L.; Costa, A.M.; Abbasi, B. Multiskilled workforce staffing and scheduling: A logic-based benders' decomposition approach. *Eur. J. Oper. Res.* **2025**, *323*, 20–33.
48. Liu, R.; Xie, X.; Augusto, V.; Rodriguez, C. Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. *Eur. J. Oper. Res.* **2013**, *230*, 475–486. <https://doi.org/10.1016/j.ejor.2013.04.044>.
49. Liu, R.; Xie, X.; Garaix, T. Hybridization of tabu search with feasible and infeasible local searches for periodic home health care logistics. *Omega* **2014**, *47*, 17–32. <https://doi.org/10.1016/j.omega.2014.03.003>.
50. van Montfort, L.; Dullaert, W.; Leitner, M. Task-splitting in home healthcare routing and scheduling. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *202*, 104235.
51. Shahnejat-Bushehri, S.; Tavakkoli-Moghaddam, R.; Boronoos, M.; Ghasemkhani, A. A robust home health care routing-scheduling problem with temporal dependencies under uncertainty. *Expert Syst. Appl.* **2021**, *182*, 115209.
52. Du, J.; Wang, X. A branch-and-price-and-cut algorithm for the home health care routing and scheduling problem with multiple prioritized time windows. *Comput. Oper. Res.* **2024**, *170*, 106749.
53. Naderi, B.; Begen, M.A.; Zaric, G.S.; Roshanaei, V. A novel and efficient exact technique for integrated staffing, assignment, routing, and scheduling of home care services under uncertainty. *Omega* **2023**, *116*, 102805.
54. Fathollahi-Fard, A.M.; Hajiaghaei-Keshteli, M.; Mirjalili, S. A set of efficient heuristics for a home healthcare problem. *Neural Comput. Appl.* **2020**, *32*, 6185–6205.
55. Hernández-Leandro, N.A.; Boyer, V.; Salazar-Aguilar, M.A.; Rousseau, L.M. A matheuristic based on Lagrangian relaxation for the multi-activity shift scheduling problem. *Eur. J. Oper. Res.* **2019**, *272*, 859–867.
56. Fikar, C.; Hirsch, P. A matheuristic for routing real-world home service transport systems facilitating walking. *J. Clean. Prod.* **2015**, *105*, 300–310.
57. Ait Haddadene, S.R.; Labadie, N.; Prodhon, C. A GRASP $\times$ ILS for the vehicle routing problem with time windows, synchronization and precedence constraints. *Expert Syst. Appl.* **2016**, *66*, 274–294.
58. Bruglieri, M.; Ferone, D.; Festa, P.; Pisacane, O. A GRASP with penalty objective function for the green vehicle routing problem with private capacitated stations. *Comput. Oper. Res.* **2022**, *143*, 105770.
59. Póvoa, C.L.R.; Roboredo, M.C.; Velasco, A.S.; Pessoa, A.A.; Paes, F.G. A hybrid GRASP and tabu-search heuristic and an exact method for a variant of the multi-compartment vehicle routing problem. *Expert Syst. Appl.* **2025**, *259*, 125319.
60. Bou Saleh, M.; Chariete, A.; Schwartz, L.; Grunder, O.; El Hassani, A.H. Reactive tabu search and mixed-integer linear programming for multi-day assignment, scheduling, and routing problems of specialised education and home-care services. *Int. J. Prod. Res.* **2024**, *63*, 1779–1802.
61. Cebeci, E.; Yücel, E.; Koç, Ç. The home health care routing with heterogeneous electric vehicles and synchronization. *OR Spectr.* **2024**, 1–42.
62. Hansen, P.; Mladenović, N.; Todosijević, R.; Hanafi, S. Variable neighborhood search: Basics and variants. *EURO J. Comput. Optim.* **2017**, *5*, 423–454.
63. Subramanian, A.; Drummond, L.M.; Bentes, C.; Ochi, L.S.; Farias, R. A parallel heuristic for the vehicle routing problem with simultaneous pickup and delivery. *Comput. Oper. Res.* **2010**, *37*, 1899–1911.
64. Yu, V.F.; Do, S.H.; Anh, P.T.; Yeh, C.T. Solving the Electric Share-A-Ride Problem Using a Hybrid Variable Neighborhood Search Algorithm. *J. Adv. Transp.* **2025**, *2025*, 6687585.

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