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PHD THESIS

# HOME HEALTHCARE SCHEDULING AND ROUTING PROBLEMS

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## ABSTRACT

HOME HEALTHCARE SCHEDULING AND ROUTING PROBLEMS

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This study introduces a new generic problem to the literature of Home Healthcare Scheduling and Routing Problem (HHSRP). Home healthcare is a cost-effective healthcare practice that can ease the burden on the healthcare system while providing comfortable service to the patients at their home environment. HHSRP involves assigning caregivers to patients and optimizing their schedules and routes to minimize total cost or the total working time of caregivers. In this new problem, multiple workers are assigned to a shared vehicle based on their qualifications and patient demands, and then the route is formed so that a traveler may be dropped off and picked up later to minimize total flow time. We introduced a mixed-integer linear programming model for the problem. To solve the problem, we developed an Adaptive Large Neighborhood Search (ALNS) algorithm with problem-specific heuristics and a decomposition-based constructive upper bound algorithm (UBA). To analyze the impact of the introduced policies, we considered some problem characteristics such as service area, difficulty of service, distribution of care, and number of demand nodes in an area. The implementation of the proposed drop-off and pick-up (DP) policy results in up to 25% reduction in total flow time compared to solutions in vehicle sharing without DP. The numerical break-even analysis showed that vehicle sharing with DP policy provides savings in total service cost, especially when demand nodes are located in small areas like in urban areas and the difficulty of service requirement increases.

**keywords:** scheduling and routing; home healthcare; workforce scheduling; vehicle sharing; drop-off and pick-up

# ÖZ


EVDE SAĞLIK HİZMETLERİ ÇİZELGELEME VE ROTALAMA PROBLEMERİ

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Bu çalışma, evde sağlık hizmeti çizelgeleme ve rotalama (ESHÇRP) literatürüne yeni bir bakış açısıyla sunulmuş bir problem önermektedir. Evde sağlık hizmetleri uygun maliyetli, sağlık sistem üzerindeki yükü hafifletirken hastalara ev ortamlarında rahat bir tedavi sunan hizmetlerdir. ESHÇRP sağlık görevlilerinin müşterilere atanması ve toplam maliyeti veya sağlık görevlilerinin toplam çalışma süresini en azlayacak çizelgeleme ve rotalama planlarının optimizasyonunu içermektedir. Bu yeni problemde, sağlık görevlilerinin yetenek ve hasta talepleri dikkate alınarak aynı araca atanmasına izin verilmektedir. Aynı zamanda, sağlık görevlilerinin, toplam akış zamanında azalma sağlandığı sürece bir hastada bırakılıp servis zamanı bittiğinde bırakılan hastadan aynı araç tarafından alınması mümkün kılınmaktadır. Önerilen bu problemin kısıtları ve varsayımlarını dikkate alan bir karma-tamsayılı lineer programlama modeli geliştirilmiştir. Ayrıca, daha büyük verilerin çözülmesini sağlayan bir Adaptif Büyük Komşuluk Arama algoritması (ABKA) ve dekomposizyon temelli bir konstrüktif üst sınır algoritması (ÜSA) geliştirilmiştir. Önerilen politikaların analizinin yapılabilmesi için yeni veri kümeleri üretilmiştir. Bu veri kümelerinde, problemin, servis alan büyüklüğü, servisin zorluğu ve toplam talep düğüm sayıları gibi özellikler dikkate alınmıştır. Önerilen bırak-al politikasının, bırak-al politikası olmayan çözümlere kıyasla ortalama %25 iyileştirme sağladığı görülmüştür. Yapılan başa-baş nokta analizleri, bırak-al politikasının toplam operasyonel maliyetleri, servis alanının daha küçük ve servis zorluğunun daha yüksek olduğu durumlarda klasik politikalara göre azalttığını göstermiştir.



**Anahtar Kelimeler:** çizelgeleme ve rotalama, evde sağlık hizmetleri, işgücü çizelgeleme ve rotalama, araç paylaşımı, bırak-al politikası

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Gökberk Özsakallı
İzmir, 2023

# TEXT OF OATH

I declare and honestly confirm that my study, titled "Home Healthcare Scheduling and Routing Problems" and presented as a PhD Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Gökberk Özsakallı

22.11.2023

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## SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| ALNS | Adaptive Large Neighborhood Search |
| AVNS | Adaptive Variable Neighborhood Search |
| CPP | Carpooling Problem |
| CP | Constraint Programming |
| DARP | Dial-a-Ride Problem |
| DSS | Decision Support System |
| DP | Drop-off and Pick-up |
| HHC | Home Healthcare |
| HHDSS | Home Healthcare Decision Support System |
| HHSRP | Home Healthcare Scheduling and Routing Problem |
| HHSRP-VS | HHSRP with Vehicle Sharing |
| ICT | Information and Communication Technologies |
| LNS | Large Neighborhood Search |
| MILP | Mixed-Integer Linear Programming |
| PDP | Pickup and Delivery Problems |
| SE | Sharing Economy |
| TSP | Travelling Salesman Problem |
| UBA | Upper-Bound Algorithm |
| VNS | Variable Neighborhood Search |
| VPSP | Vehicle and Path Sharing Problem |
| VRP | Vehicle Routing Problem |
| VRPTW | VRP with Time-Windows |
| VS | Vehicle Sharing |
| WSRP | Workforce Scheduling and Routing Problem |
| WHO | World Health Organization |

# CHAPTER 1
# INTRODUCTION

This thesis aims to propose a novel variant of home healthcare scheduling and routing problem (HHSRP) to the existing literature. Home healthcare (HHC) services encompass a diverse range of medical and clinical care provided to patients within their own homes. According to World Health Organization (WHO, 2015), the type of healthcare services that HHC can provide summarized as medical and psychological assessment, wound care, medication education, pain and disease management, and physical therapy. The provision of these services is carried out by healthcare professionals who meet the necessary qualifications. HHC can also be viewed as a form of transitional care in which it provides supplementary healthcare services for discharged patients in need of ongoing medical treatments.

The demand for HHC services has been steadily rising all around the world. One of the main reasons of the increase is closely associated with the ageing population, the increase in the percentage of elderly people, and increasing life expectancy. It is estimated that the number of elder people is projected to more than double reaching over 1.5 billion people over the age of 65 in 2050 (United Nations, 2019). Additionally, increase in the ageing population has also changed the burden of illnesses from acute life-threatening diseases to chronic disabling diseases (WHO, 2015). This shift poses significant challenges that needs to be addressed by governments and healthcare systems due to the associated increase in long-term care and medical costs (Crimmins, 2004). Consequently, HHC services have emerged as an important alternative to traditional healthcare systems. According to U.S. Labor's projections for 2014-2024, home healthcare services are expected to grow 60% with an additional 800 thousand new jobs. HHC can provide personalized services at low cost, not only for the elderly or disabled people but also to individuals those requiring assistance during recovery from an illness or injury in a familiar environment after getting treatment at the hospital.

Furthermore, during the recent global pandemic of COVID-19, HHC workers have played an essential role as frontline personnel in various countries (Bowles et al., 2021).

In addition to attending to routine and private healthcare requirements of patients who are unable or disinclined to seek hospital-based care due to the inherent risk of contracting COVID-19 (Sama et al., 2021), the HHC workers had undertaken the responsibility of administering a wide range of healthcare services to COVID-19 patients. These patients, who either received home-based treatment or were discharged from hospitals and require medical care in self-isolation protocols, received necessary medical care and support from HHC workers within the familiar environment of their own residences.

For these reasons, researchers have been increasing their attention to design efficient HHC systems and find improved management approaches by engaging in decision-making processes at different stages of the system. HHC systems consist of three primary groups which are healthcare providers, caregivers, and patients. The problem becomes extremely complex when considering the diverse and multifaceted preferences and constraints of each group. Healthcare providers must consider crucial factors such as the geographical region of HHC service provision, the number and qualification of caregivers, service quality, and overall operational costs. Furthermore, caregivers are typically bound by diverse contractual arrangements that determine salaries and working hours, alongside their distinct areas of expertise which dictate the scope of medical services they can provide. Lastly, patients introduce key constraints including the type of medical treatments required, preferred time windows for service delivery, and personal preferences. As these multifarious elements are considered, the complexity of the HHC system increases exponentially (Polnik et al., 2021).

HHC systems have three level problems, including strategic, tactical, and operational. Location planning, territory partitioning and resource allocation to the territories are strategic level problems that need to be considered. Tactical level consists of demand forecasting and resource dimensioning problems. A recent literature review on the strategic and tactical level studies is published by Chabouh et al. (2023). Two main problems need to be solved every day by decision-makers at HHC institutions at the operational phase. The first problem is an assignment problem which involves determining the appropriate allocation of caregivers to patients based on considerations of caregivers' skills and specialties, as well as patients' specific requirements. The second problem involves scheduling and routing of these assigned caregivers, which is referred to as the home healthcare scheduling and routing problem

(HHSRP) in the literature. In the literature, these two problems are considered simultaneously with the help of Operations Research tools. Consequently, in the HHSRP, decision-makers try to find an efficient route and schedule for caregivers while simultaneously assigning them to patients with the objective of minimizing travel and service costs.

However, mismanagement in scheduling and routing caregivers can lead to unserved or delayed patients, patient dissatisfaction, increased working hours for caregivers, and high travel and service costs. For instance, according to Holm and Angelsen (2014), caregivers in Norway spend approximately 18% to 26% of their working time traveling in vehicles. Consequently, they face a heightened risk of motor vehicle-related injuries and a potential loss of productivity due to time spent driving (Weerdt and Baratta, 2015).

In this study, a novel vehicle sharing policy is proposed to minimize total operational costs and increase the efficiency of HHC providers. The proposed policy allows caregivers to share the same vehicle when visiting patients. To the best of our knowledge, the existing literature does not explore the vehicle sharing approach among caregivers. By enabling the vehicle sharing, the number of required vehicles to operate the system can be significantly reduced. However, it is important to address potential drawbacks such as unnecessary waiting times for caregivers which can decrease their productivity. To mitigate the issue, a "drop and pick-up policy" is proposed, allowing caregivers to be dropped off be the vehicle at a patient's location to minimize waiting times, and subsequently picked up by the vehicle once their service is completed. These proposed policies introduce a new vehicle sharing approach for HHSRP literature.

The problem addressed in this study is referred to as the Home Healthcare Scheduling and Routing Problem with Vehicle Sharing (HHSRP-VS). The novel vehicle sharing approach presented herein contributes not only to the existing HHSRP literature but also to the broader field of workforce scheduling and routing problem (WSRP).

To examine the effectiveness of the policy across various scenarios, a mixed-integer linear programming is formulated, taking into account both vehicle sharing and drop and pick-up policies. However, due to the extension of these additional policies, HHSRP-VS becomes extremely complex and challenging to solve. Therefore, this study introduces two solution approaches to tackle this complexity: a constructive matheuristic upper-bound algorithm and an Adaptive Large Neighborhood Search (ALNS) algorithm with problem-specific local search heuristics. These algorithms are designed to generate efficient solutions for the HHSRP-VS, overcoming the computational difficulties posed by the extended policies. In addition, a Home Healthcare Decision Support System (HHDSS) is presented in this study. HHDSS is designed to support HHC planners with the daily task of scheduling and routing of caregivers. The HHDSS employs the proposed algorithm to optimize the caregivers' routes. It is tested on instances generated using data of COVID-19 patients from the biggest cities of Turkey.

# CHAPTER 2
# HOME HEALTHCARE SCHEDULING AND ROUTING PROBLEM WITH VEHICLE SHARING

Despite gaining popularity two decades ago, the provision of HHC services has a historical foundation dating back several centuries. Informal HHC services were traditionally provided by family members, religious institutions (Tarricone and Tsouros, 2008), as well as traveling physicians and nurse-midwives (Işık, 2016). During the 19th century, hospital care served as the primary source of healthcare for older individuals, children, disabled individuals, and those with mental disorders. However, efforts to reduce long-term hospital stays for the elderly and children, while improving the quality of home care, have been underway since the 1960s (Tarricone and Tsouros, 2008). Alternative approaches such as community care, continuous care, and home-based care have been proposed to alleviate the dependence on hospital-based care.

Additionally, changes in lifestyle trends (Jacobzone et al., 1999), smaller family sizes (Nasir and Dang, 2020), and increased labor market participation by women (Tarricone and Tsouros, 2008) have contributed to a decline in the provision of informal home care (Genet et al., 2011). Consequently, the growing demand for care resulting from an aging population, coupled with the diminished availability of informal care, has led to the expansion of formal home healthcare services.

The terms "home care" or "social care" and "home healthcare" are often used interchangeably in the literature. However, the distinction between home care and home healthcare lies in the nature of the services provided at home (Tarricone and Tsouros, 2008). Home care encompasses household tasks such as shopping, cooking, and cleaning, as well as socialization and personal care such as assistance with dressing and bathing. These activities serve as substitutes for informal care and are typically provided by social service sectors or family members, predominantly catering to older individuals. On the other hand, home healthcare services primarily involve rehabilitation, physical and occupational therapy, health promotion, disease prevention, and physiotherapy (see Table 2.1).

**Table 2.1.** Differences between home care and HHC

| Home Care Services | HHC services |
|---|---|
| Companionship | Physical and occupational therapy |
| Assistance with activities of daily living | Medical tests |
| Meal preparation or delivery | Administration of prescription medications or shots |
| Transportation to appointments | Monitoring of health status |
| Cleaning and organizing | Wound care |

## 2.1. Home Healthcare Systems in Turkey

In Turkey, the foundations of HHC services were established in 1961 with the Socialization of Health Services law. This legislation emphasized the importance of centralizing healthcare services, ensuring an equal distribution of caregivers across the country, and extending HHC services to rural areas with insufficient hospital bed capacity. However, the implementation of HHC services similar to those introduced in developed Western countries only began in 2005 with the adoption of the Healthcare Transformation Program. The Home Care Service Delivery Decree was subsequently published in the Official Gazette on March 10, 2005, which outlined the regulations for healthcare institutions offering home care services as an independent business activity or as part of medical centers, specialized centers, polyclinics, or private hospitals. Changes made to the Disability Law and Other Statutory Decrees on July 1, 2005, also emphasized the preference for home-based disability care whenever possible, with the state covering the cost of home care for eligible individuals.

The Ministry of Health published the Directive on the Procedures and Principles of Home Healthcare Services in 2010, with the aim of providing examination, testing, treatment, medical care, rehabilitation services, and comprehensive social and psychological support within the familial atmosphere of patients' homes. Home healthcare services are offered by educational and research hospitals, home healthcare service units within general or specialized hospitals, social health centers, family health centers, and family doctors. The coordination and management of these services, along with communication and collaboration among units, are facilitated through a coordination center established within the directorate, supervised by a healthcare associate director.

Finally, the Regulation on the Presentation of Home Healthcare Services was published by the Ministry of Health in 2023. This new regulation introduces various key changes and developments in the provision of HHC services. The scope of HHC service provision has been expanded, with the establishment of standards regarding personnel, vehicle, and equipment capacity to meet the increasing demand. Additionally, the standardized requirements for both short-term and long-term HHC services, and eligible patient groups are defined.

## 2.2. Key Characteristics of Home Healthcare System

As stated by many studies (Carpenter et al., 2004; Genet et al., 2011; Kristinsdottir et al., 2021) the definition and scope of HHC can significantly vary between countries as well as within countries (MacAdam, 2004; van Hout et al., 2019). This subchapter examines the key characteristics of HHC systems across different countries. The various aspects of HHC systems can be analyzed under three key characteristics: the type of HHC providers, the sources of funding, and regulation of HHC benefits. A comprehensive discussion on this topic can be found in (Genet et al., 2011; Genet et al., 2012a and van Enoo et al., 2016).

### 2.2.1. Type of Providers

Different kind of HHC service provider models can be found in each country, including public, private (both not-for-profit and for-profit) organizations, and a mix of these. The provision of HHC services is predominantly carried out by non-profit organizations in both the public and private sectors. The exception is observed in Germany, where 63% of the organizations are private for-profit (van Enoo et al., 2016). However, it is stated that the share of private for-profit providers shows an increasing trend for the service provision in the other countries including England (Netten et al., 2007), Ireland (Timonen and Doyle, 2008), Sweden (Sundström et al., 2002), as well as Turkey (Aslan et al., 2018). Additionally, even though private service provision is growing in the Netherlands, there is also a notable emergence of a new trend of neighborhood-centered HHC services. This trend has developed in response to the dissatisfaction of professional providers (Genet and Boerma, 2012). Kendall et al. (2003) and Bode (2006) argue that the introduction of market mechanisms has resulted in the weakening of non-profit organizations. On the other hand, for-profit providers have demonstrated greater adaptability to the changes.

According to Genet et al. (2012b), there are three types of government models on regulating provision of HHC services defined as centralized type, framework type, and laissez-faire type. Centralized type is defined by the prominent role of the central government which regulates the scope of services and strict eligibility criteria. Regional authorities are primarily responsible for implementing the policies set by the central government. Framework type is characterized by a combination of national regulations, and decentralized decision making. Often, general principals are defined without strict boundaries. Therefore, the provision of HHC services may vary largely within the countries. Lastly, unlike the centralized type, the central government has minimal role in the regulations of the services in the laissez-faire type. However, lack of regulations on private providers may result in provision of poor quality services, and inequalities in the working conditions of HHC workers (Netten et al., 2007; Timonen and Doyle, 2008). The summary of different governance types can be found in Table 2.2.

### 2.2.2. Sources Of Funding

In general, different types of sources are used for funding public HHC systems, including general taxation, budgets of municipalities, private payments, and social insurances (Genet et al., 2011). Taxes serve as primary public funding source in most of the countries such as Denmark (Stuart and Hansen, 2006), Portugal (Santana et al., 2007), and Iceland (Hutchinson, 2012), with the exception of Germany.

The other mainly used public funding source is social insurance. HHC is funded through either part of the compulsory health insurance as seen in the Netherlands (Genet and Boerma, 2012) and in Germany (Garms-Homolovà, 2012) or as part of social security.

**Table 2.2.** Main Types of HHC governance

| Centralized | Framework | Laissez-faire |
|---|---|---|
| | ***Features*** | |
| Dominant role of national government. Detailed entitlements set by national government. National vision on home care | Non-state actors have wide decision-making power.<br>National vision on home care | Weak role of central government.<br>No government vision.<br>Few entitlements |
| | ***Actors*** | |
| Central government lays down detailed regulation.<br>Municipal or regional government has main involvement in operational activities.<br>Private providers may be strictly regulated. | Central government lays down regulation along broad lines.<br>Municipal or regional governments have large discretionary powers.<br>NGOs may have large roles. | NGOs setting their own rules or contracted sporadically by government.<br>Private providers setting their own rules and helping those who can afford.<br>Government for most severe cases. |
| | ***Main policy issues*** | |
| Efficiency.<br>Maintaining equity | Equity | Equity.<br>Quality in general |

*Note.* From Genet et al. (2012b), p.38.

In general, only certain HHC services is eligible for public funds. For example, HHC services are nationally funded for elderly people in France (Litwin and Attias-Donfut, 2009) as well as in Turkey. On the other hand, Otero et al. (2003) argue that private organizations are necessary for the provision of the services in Spain due to the limited availability of public sources for the HHC service coverage.

### 2.2.3. Regulation of HHC benefits and workers

Provision of HHC services is dependent on a set of eligibility criteria. In most of the countries, elderly people are primary eligible recipients of these services. The eligibility criteria typically consider the financial situation and medical condition of the patient and the availability of the informal care (Bihan and Martin, 2006; van Hout et al., 2019), and it is stated that the assessment process is stricter in France compared to other European countries. HHC services are independent from the income of the patients and are considered as universal in certain countries such as Scandinavian countries and Turkey (Genet et al., 2011). On the other hand, age also is considered as eligibility criteria in addition to the financial situation.

HHC is highly demanding for HHC workers (Totterdell and Holman, 2003). Caregivers often face increased risk of motor vehicle related injuries due to driving from patient to patient (Weerdt and Baratta, 2015). Additionally, they are prone to back injuries and musculoskeletal disorders (Owen and Staehler, 2003; Waters et al., 2006). Caregivers also frequently experience burnout (Meissner et al., 2007; Xanthopoulou et al., 2007). Hence, it becomes crucial to regulate the working conditions of HHC workers in order to increase the job satisfaction and reduce worker turnover rates.

## 2.3. Strengths and Weaknesses of Home Healthcare Systems

In this subchapter, the strengths, and weaknesses of HHC systems as an alternative to institutional care are examined. Several studies state that provision of HHC services has positive effect on patient safety and quality of living while reducing mortality rates and costs (Caplan et al. 2012; DeCherrie et al., 2022).

Early studies state that providing healthcare services to patients in the home environment is significantly cost effective than the provision of the same service in a hospital (Hammond, 1979; Jones et al., 1999). However, the benefits of HHC systems in terms of cost-effectiveness depends on the condition of patients and the provided services (Soderstrom et al., 1999). Anttila et al. (2000) shows that the implementation of post-discharge HHC for elderly population resulted in a cost reduction of 24% to 52% for university hospital. Similar finding reported in Miller et al. (2005) that an early discharge rehabilitation program is cost-effective. Hammar et al. (2009) concludes that integration of HHC services and discharge practices tend to be cost effective. According to O’Dell and Wheeler (2012), HHC systems are found to be cost effective compared to extended hospitalization, and it is almost same to long-term stay hospital stays.

Moreover, one of the most important features of HHC services is the personalized healthcare service provision. Personalized attention of caregivers in the home environment improves the patient satisfaction (Hughes et al., 2000; Vass et al., 2005). Also, most of the studies in the HHSRP literature incorporate patient preferences into their models to maximize this criterion (Eveborn et al., 2006; Rasmussen et al., 2012).

HHC services also improves the quality of living which often helps to improve recovery time (Owen et al., 2015). In addition, Elkan et al. (2001) finds that HHC is effective in reducing mortality rates and admission to long-term hospitalization for elder populations. Similar finding reported in Tomita et al. (2010) that HHC services would prevent hospitalization of elderly people with the improvements on the physical and mental conditions. Ishibashi and Ikegami (2010) demonstrates the positive impact of HHC services in functional decline among elderly population who receives HHC services.

The risk of HHC related infections is a controversial topic in the literature. Haque et al. (2020) states that hospital associated infection rate is between 5% to 15% in high income countries, and 10% of these patients die. On the other hand, Shang et al. (2015) finds that an average of 3.5% of patients developed infections while receiving HHC services resulting in the need of emergency care or hospitalization in the United States. This risk also intensified during and after COVID-19 pandemic, as expected (Burgdorf et al., 2022). Therefore, it is extremely important to incorporate predictive risk models in HHC services to prevent potential hospitalizations and emergency treatments (Shang et al., 2020; Song et al., 2022).

One of the main limitations of HHC services is the restricted variety of services that can be offered in emergency situations. The services can be provided by HHC systems are often preventative and health promoting services rather than acute emergency care (Keating, 1995). This restriction can pose serious challenges. Madigan (2007) and Sears et al. (2013) find that 13% of HHC patients experience at least one adverse event with one-third of these incident being preventable. HHC providers have responsibility for implementing necessary strategies to increase safety of both patients and caregivers, and to prevent avoidable unwanted events. Furthermore, effective communication and attention from caregivers also play a vital role (Coleman, 2003; Romagnoli et al, 2013).

Caregivers in general are lack of specialized training in providing care for patients in a home setting (WHO, 2015; Miller et al. 2022). It is crucial for patients to receive not only medical care but also support in addressing their social and psychological needs. Therefore, high level of communication skills and patient support are desired in HHC services (Işık et al., 2016). However, Cunningham et al. (2020) states that training and education of caregivers pose challenges in HHC systems. Despite the challenges, there are studies that propose training programs to enhance skills of caregivers that shows promising results (Brown et al., 2010; Clair et al., 2019; Goroncy et al., 2020).

Finally, caregivers face risks due to inherent uncertain nature of the home environment during the HHC visits. Caregivers are exposed to potential risks such as violence, verbal abuse, and unhealthy home conditions during the provision of the care. Canton et al. (2009) highlights the risk of violence towards caregivers, while Karlsson et al. (2019) emphasizes the occurrence of verbal abuse. Additionally, Gershon et al. (2012) discusses the potential hazards associated with unsanitary homes. Quinn et al. (2021) provides a comprehensive review on weaknesses and challenges of HHC services and offers valuable guidelines for the improvement. Strengths and weaknesses of the HHC systems are summarized in Table 2.3.

**Table 2.3**. Strengths and weaknesses of HHC

| Strengths | Weaknesses |
|---|---|
| Cost effective | Needs special training |
| Improved quality of living | Needs high level of communication |
| Reduced mortality rates | Limited range of services in emergency situations |
| Reduced infection risks in specific services | Risks due to unpredictable nature of home environment |
| More appealing to patients | Risk of vehicle related injuries |

## 2.4. Future of Home Healthcare

HHC has emerged as a popular alternative to hospital-based care. The advantages of HHC services are summarized in this chapter such as cost-effectiveness and reduced risk of hospital associated infections etc. In addition, with the global shift in illnesses from acute life-threatening diseases to chronic disabling diseases (WHO, 2015) with the increase of ageing population, HHC services has become one of the most preferable healthcare services. It is stated that HHC has been the fastest growing sector healthcare sector for the past 3 decades (Jarvis, 2001; Markkanen et al., 2007; Shang et al., 2014). Since the proportion of 65+ older is expected to increase from 16% to 27.8% in 2050 (Kristinsdottir et al., 2021), this trend of growth is expected to continue. According to U.S. Labor of Department (2015), HHC services are expected to grow 60% by 2024.

# CHAPTER 3
# HOME HEALTHCARE SCHEDULING AND ROUTING PROBLEM WITH VEHICLE SHARING

Two distinct features of the HHSRP-VS are (1) multiple independent caregivers, who can provide independent services to different patients, traveling in the same vehicle and (2) a drop-off and pick-up (DP) policy implemented on a trip. Hence, the main objective of this research is to answer the following research questions.

i. How effective are variations of the proposed caregiver swap heuristic used in the proposed ALNS algorithm?
ii. How effective and efficient are the proposed upper bound and ALNS algorithms compared to each other and to CPLEX solutions?
iii. How effective is the DP policy in HHSRP-VS? Under which circumstances does DP policy provide savings on total flow time?
iv. How effective is vehicle sharing policy in HHSRP-VS? Under which circumstances does vehicle sharing with DP policy provide savings on total flow time and total service cost?

In this section, we first provide an extensive literature review and then formal description of the problem. The section is concluded with the proposed mixed-integer linear programming model of HHSRP-VS.

## 3.1. Literature Review

As discussed in the previous chapter, HHC service providers offer a wide range of services to a person in need. For this purpose, staff (caregivers) with different qualifications like general physicians, therapists, nurses, social workers, dietitians, psychologists, etc. are employed by the providers. To travel between different patients' locations and HHC centers, these caregivers either have their personal vehicles or use a vehicle provided by the HHC service providers. The patients require certain types of services, which must be performed by suitably qualified staff members. One of the main problems facing the management of the HHC service provider is the daily scheduling and routing task (Borchani et al., 2019). This scheduling and routing determine which visit will be performed, by which caregivers, and by which vehicles (if personal vehicle is not the case).

### 3.1.1. Workforce Scheduling and Routing Literature

The daily scheduling of tasks and routing of caregivers in the HHC service is an example of WSRP (Bredström and Rönnqvist, 2008). WSRP can be modeled as a vehicle routing problem (VRP) with the presence of some uncommon constraints (Cissé et al., 2017). According to Castillo-Salazar et al. (2016), assignment and scheduling of tasks to teams or to individual workers in WSRP are done on two different grounds. The first is that all workers have the same qualifications in which any worker can be assigned to any job. This can be seen in the problem of scheduling and routing security guards (Alfares & Alzahrani, 2020), electricity network maintenance (Goel & Meisel, 2013), etc. On the other hand, there are scenarios in which a workforce with different qualifications/skills is required and these qualifications should be satisfied with the schedule. Examples of this are common in industries like network infrastructures (Guastaroba et al., 2021), electricity distributions (Çakırgil et al., 2020), home healthcare (Liu et al., 2017), and so forth. In the WSRP, the demands are satisfied by either a team or an individual worker. The main distinction between WSRP and HHSRP is team formation, which might be required based on the nature of the tasks to be performed (Li et al., 2005). In general, the teams are formed at the beginning of the planning horizon as to meet the requirements of the tasks and can therefore be considered as a single entity (Cordeau et al., 2010; Anoshkina and Meisel, 2019; Punyakum et al., 2022). In the context of HHSRP, teaming is not a typical assignment constraint. WRSP is NP-Hard as it is a variant of VRP. Therefore, the majority of the studies in the literature consist of heuristic and matheuristic algorithms (Guastaroba et al., 2021). In addition, exact algorithms typically formulate the problem as a set covering or partitioning model and solve it using branch-and-price algorithms (Zamorano and Stolletz, 2017; Schrotenboer et al., 2019; Su et al., 2023).

### 3.1.2. Home Healthcare Scheduling and Routing Literature

To the best of our knowledge, Begur et al. (1997) and Cheng and Rich (1998) were the first to handle the HHSRP. Using the nearest neighborhood search heuristic approach, Begur et al. (1997) modeled the problem as a VRP without considering time-window constraints and shared visits. On the other hand, Cheng and Rich (1998) modeled the problem as a VRP with time-window constraints (VRPTW) using a the mixed-integer linear programming (MILP) and proposed a simple solution heuristic. Since Begur et al. (1997), researchers have been developing models and solution algorithms for solving the variants of HHSRP. The literature on HHSRP is extensive with review papers that provide detailed overviews and analyses of the existing research. Comprehensive literature reviews were published recently by Di Mascolo et al. (2021), Grieco et al. (2021) and Goodarzian et al. (2023). In addition, literature reviews of Cisse et al. (2017), and Fikar and Hirsch (2017) provide detailed information about fundamental characteristics of the problem and well-known studies in the literature.

As in the work of Cisse et al. (2017), constraints are grouped into three main categories which are temporal constraints, spatial constraints, and assignments constraints. Each category has one or more specific features. In the following, brief information about type of constraints is given. In addition, some of the important studies regarding HHSRP are briefly summarized according to their features in Table 3.1.

***The planning horizon*** determines the period in which scheduling and routing plan is made. According to Cisse et al. (2017), the length of the plan depends on the availability of demand information. In the literature, mostly a single-day planning horizon is considered due to the quality of the information (Eveborn et al., 2006; Redjem and Marcon, 2016; Rest and Hirsch, 2016; Pinheiro et al., 2016; Qiu et al., 2022). On the other hand, studies that consider multi-period planning horizon generally consider one week planning horizon (Begur et al., 1997; Trautsamwieser and Hirsch, 2014; Qin et al., 2015; Wirnitzer et al., 2016; Chen et al., 2016; Pereira et al., 2020). In addition, ***continuity of care*** is an important service quality indicator for HHSRP environment. Continuity of care constraint is not always but in general considered in multi-period HHSRP setting in which patients consistently receive the service by the same caregiver (Wirnitzer et al., 2016; Fathollahi-Fard et al., 2021; Nikzad et al., 2021). In HHSRP context, this constraint builds a relationship of confidence between the patient and caregiver (Cisse et al., 2017).

***Qualification of caregivers*** is one of the most important characteristics of HHSRP. This is because the service providers must match the patients' varying requests with the employees' expertise. In the literature qualification of caregivers is considered in two ways. In the first one, more than one qualification can be assigned to a worker (Eveborn et al. 2006; Rasmussen et al. 2012; Pillac et al., 2013; Bard et al. 2014; Mankowska et al. 2014; Liu et al. 2017; Mathlouthi et al., 2021). Whereas in the second approach, it can be determined based on the hierarchical level of qualification (Cordeau et al., 2010; Nickel et al. 2012; Rest and Hirsch 2016; Trautsamwieser and Hirsch 2011) in which each patient's demand has a minimum required level of qualification and each caregiver is associated with some qualification level. In our study, we considered the first type of qualification approach in which the demand and the skill should be matched.

***Maximum working time for caregivers*** defines the maximum amount of time a caregiver is allowed to work in a shift, which is usually implemented by setting a time window. Maximum working time constraint can be a hard constraint (Bredström and Rönnqvist,2008; Frifita et al., 2017; Rasmussen et al.,2012; Trautsamwieser and Hirsch, 2014; Goodarzian et al., 2021) with a penalty cost for unvisited or missed patients, or a soft constraint which allows ***overtime*** with an additional cost in the objective function (Cheng and Rich, 1998; Rest and Hirsch, 2016; Trautsamwieser and Hirsch, 2011; Gong et al., 2020; Malagodi et al., 2021). In our study, we considered hard maximum working time constraints.

***Time windows of patients*** denotes the suitable time intervals that patients accept visits. It is assumed that patients have time windows in most of the HHSRP studies (Cheng and Rich, 1998; Eveborn et al., 2006; Rasmussen et al., 2012; etc.). Time windows can be applied in two different ways. Hard time windows impose that arrival to a patient after the upper bound of the window is not allowed. On the other hand, soft time windows (Trautsamwieser and Hirsch, 2011) allow the late arrivals with a penalty cost. In addition, Mankowska et al. (2014) propose mixed time windows of patients. In this approach, starting time of the service cannot exceed the earliest starting time. However, tardiness of service is allowed which means that a service can start after the latest starting time with a penalty cost.

In the HHSRP literature, multiple caregivers are only seen in the studies that consider ***temporal dependency*** constraints: ***synchronization*** and ***precedence***. Synchronized/shared services require visits of different caregivers at the same time (Eveborn et al., 2006; Issabakhsh et al., 2018; Frifita et al., 2017; Liu et al., 2021). The precedence constraint prioritizes multiple services (Liu et al., 2013; Bard et al., 2014), which are very necessary in the case when one of the two services of a patient should be performed before the other. Several studies considered both type of temporal dependency constraints (Bredström and Rönnqvist, 2008; Rasmussen et al., 2012; Mankowska et al., 2014; Shahnejat-Bushehri et al., 2021). Although these studies, especially the ones that are considered synchronization constraints, require multiple workers, they either travel with their own vehicle and meet the patient at the same time or travel as a team to perform the same task. Thus, according to the best of our knowledge, it can be said that no study considers routing of multiple independent caregivers in a shared vehicle.

### 3.1.3. Sharing Economy and Vehicle Sharing Literature

The sharing economy (SE) has emerged as a transformative force in recent years. While the SE emerged around 2008-2009, early examples of online platforms such as Craigslist and eBay facilitating the sharing of goods and information were established in 1995 (Schor and Fitzmaurice, 2015). This dynamic economic model, characterized by the efficient utilization of underutilized assets and resources, has significantly altered traditional consumption patterns and service delivery mechanisms (Schor and Vallas, 2021). According to the review paper by Cheng (2016), the rapid expansion of the SE over the last two decades is closely tied to socioeconomic factors, driven by the desire for better and more equitable value distribution in supply chains (Gansky, 2010), efforts to decrease environmental footprints (Schor and Fitzmaurice, 2015), advancements in technology, and shifts in consumer attitudes regarding product ownership and the importance of social connection (Botsman and Rogers, 2010). Accommodation sharing (Dogru et al., 2020) and mobility sharing (Standing et al., 2019) are the most common forms of the SE. Shared mobility refers to the collaborative utilization of transportation methods, allowing individuals to access transportation as necessary for short periods (Mouratidis et al., 2021). Modern shared mobility is greatly aided by information and communication technologies (ICT) and mobile applications (Gössling, 2018). It includes a range of services, including carsharing, bikesharing, ridesharing (carpooling and vanpooling), ridesourcing (on-demand ride services), and e-scooter sharing.

**Table 3.1.** Summary of relevant studies in the literature

| Reference | Planning horizon | Time windows | Maximum working time | Overtime | Continuity of care | Qualification | Synchronization | Precedence | Preference | Workload balance | Vehicle Sharing | Solution Algorithm |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cheng and Rich (1998) | Single | * | | | | | | | | | | Heuristic |
| Eveborn et al. (2006) | Single | * | | | * | * | * | | * | | | Repeated matching |
| Akjiratikarl et al. (2007) | Single | * | * | | | | | | | | | Particle swarm |
| Bredstörm and Rönnqvist (2008) | Single | | * | | | | * | * | * | | | Matheuristic |
| Trautsamwieser and Hirsch (2011) | Single | * | * | * | | * | | | * | | | VNS |
| Nickel et al. (2012) | Multi | * | * | * | * | * | | | | | | CP with Heuristics |
| Rasmussen et al. (2012) | Single | * | * | | | * | * | * | * | | | Branch and price |
| Mankowska et al. (2014) | Single | * | | | | * | * | * | | | | AVNS |
| Trautsamwieser and Hirsch (2014) | Multi | * | * | | | * | | | | | | Branch and price and cut |
| Redjem and Macron (2016) | Single | * | | | | | | * | | | | Heuristic |
| Rest and Hirsch (2016) | Single | * | * | * | | * | | | | | | Tabu search |
| Wirnitzer et al. (2016) | Multi | * | * | * | * | | | | * | | | MILP |
| Fathollahi-Fard et al. (2021) | Multi | * | * | | * | * | | | | * | | Hybrid metaheuristic |
| Goodarzian et al. (2021) | Multi | * | * | | | * | | | | * | | Metaheuristic |
| Malagodi et al. (2021) | | | * | * | | * | | | * | | | Cluster based decomposition |
| Nikzad et al. (2021) | Multi | * | * | | * | * | | | | | | Progressive hedging based matheuristic |
| This Study (2023) | Single | | * | | | * | | | | | * | ALNS |

VNS: Variable neighborhood search. CP: Constraint programming. AVNS: Adaptive variable neighborhood search. ALNS: Adaptive Large Neighborhood Seach

Different terms have been used for vehicle and path sharing (VPSP) in the VRP and WSRP literature such as, dial-a-ride, ride-sharing, taxi-sharing, carpooling, etc. All of these problems are the special cases of pickup and delivery problems (PDP) (Agatz et al., 2012) that contain the special case of VRP (Nalepa & Blocho, 2017), therefore are located in the NP-Hard class. According to Castillo-Salazar et al. (2016), the PDP cannot be considered as a WSRP because in terms of time no significant "work" is done within the premises of the customer in the PDP. In PDP, vehicles have to transport loads directly from one location to another (Savelsbergh & Sol, 1995). Recker (1995) proposed an interesting extension of pickup and delivery for household activity pattern problems which involves ride-sharing along with vehicle-switching options. The objective of the study was to minimize the disutility of household travel, but no solution methodology was developed for the problem by the author. The dial-a-ride problem (DARP), which was firstly proposed by Cordeau and Laporte (2003), focuses on planning the routes of vehicles and their schedules for the transportation of multiple passengers who request to travel from a specific place to some destination. For the convenience of the passengers, different standard measures are used either as a set of constraints or in an objective function in the mathematical model. Some of the standard measures are waiting time, the number of stops during travel, etc. (Paquette et al., 2009).

Baldacci et al. (2004) interpret the carpooling problem (CPP) based on DARP and propose exact and heuristic methods to solve the to-work variant of the problem which was based on two integer programming formulations. Lin et al. (2012) formulated a taxi ride-sharing system based on DARP for picking up and dropping the customers off at different locations. The main contribution of the study is the inclusion of the customers' satisfaction in the objective as the minimum waiting time for the customer to be picked. Simulated Annealing algorithm was used as a solution strategy that was capable of solving instances with up to 29 customers. Dynamic ride-sharing problems differ from the conventional one in such a way that they intend to bring together travelers with similar itineraries and time schedules on short-notice (Agatz et al., 2012). For a comprehensive review of the literature on ride-sharing, we refer Mourad et al. (2019) for interested readers.

In all of the abovementioned studies, mainly commuters or their vehicles are routed. Unlike in WSRP or HHSRP, there is no such constraint or requirement as a service time of a job, workers' qualifications, worker-to-task (caregiver-to-patient) assignment etc. However, in this study multiple travelers are assigned to a shared vehicle according to the demand and their characteristics, and then the route is formed such that a traveler may be dropped and picked up later to minimize total route length. Thus, the introduced problem in this study combines the characteristics of WSRP or HHSRP and VPSP and provide some special features.

## 3.2. Problem Definition and Mathematical Model

In this section, we first provide a formal description of the problem and then MILP formulation. The HHSRP-VS is defined as the complete directed graph $G = (V, A)$, where $V = \{0,1, \dots, n, n+1, \dots, 2n, 2n+1\}$ is the set of all nodes in the graph and $A = \{(i,j): i,j \in V, i \neq j\}$ is the set of arcs between every pair of nodes excluding arcs between the same nodes. $n$ is the number of patients, and nodes 0 and $2n+1$ indicate the same beginning and ending HHC center. The set of caregivers and illnesses (types of cares) are denoted by $L = \{1,2, \dots, \bar{l}\}$ and $S = \{1,2, \dots, \bar{s}\}$, where $\bar{l}$ and $\bar{s}$ are the numbers of available caregivers and type of illnesses that can be treated, respectively. Last, $K = \{1,2, \dots, \bar{k}\}$ indicates the set of $\bar{k}$ vehicles.

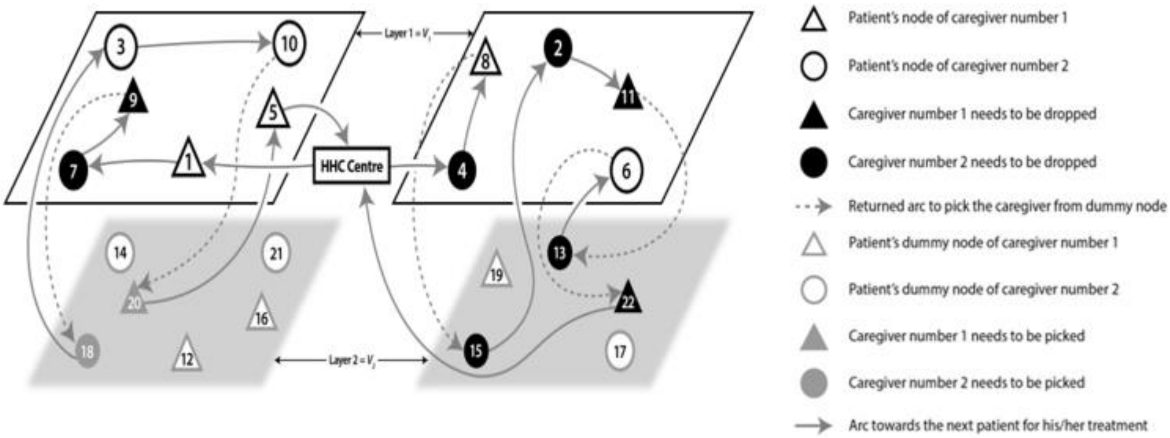



**Figure 3.1.** The two-layer representation model of the HHSRP-VS problem. The left and right routes describe the vehicles 1 and 2's routes, respectively.

The sub-tour elimination constraint, which is one of the typical constraints in VRP, cannot be enforced due to the implementation of the DP policy that leaves a caregiver to a node and then picks up from the same node. Therefore, we proposed a two-layer modeling approach to easily adapt DP policy and avoid sub-tour elimination. In this approach, $V_1 = \{1,2,3, \dots, n\}$ is defined as the set of original patient nodes, and $V_2 =$

$\{n+1, n+2, \dots, 2n\}$ is the set of their dummy nodes. For clarification, the two-layer approach is demonstrated in Figure 3.1.

As seen in Figure 3.1, the original patient nodes are placed in the first layer, and their projections are in the second layer. A vehicle can visit a dummy node in the second layer for picking up a caregiver if and only if its original patient node was visited before and the requested caregiver was dropped off at that node. Hence, this approach could also be considered as one of the methodological contributions of this study. For example, suppose that there are 11 patients, 4 distinct caregivers, and 2 identical vehicles. Each vehicle carries two distinct caregivers. Suppose that the assigned caregiver_1 in vehicle_1 will treat patients (1, 5, 9) while caregiver_2 in the same vehicle is assigned to patients (3, 7, 10). Similarly, suppose that caregivers_1 and _2 in vehicle_2 are assigned to treat patients (8, 11) and (2, 4, 6), respectively. Suppose that the optimal routes of vehicle_1 and vehicle_2 are computed as {0, 1, 7, 9, 18, 3, 10, 20, 5, 23} and {0, 4, 8, 15, 2, 11, 13, 6, 22, 23}, respectively, in which {0} and {23} indicate the start and end nodes of the single HHC center. Hence, vehicle_1 starts its travel with two caregivers and visits directly to patient 1 where only caregiver_1 provides care. The vehicle and caregiver_2 wait for caregiver_1 to finish his/her service. Next, they travel to patient 7 where caregiver_2 is being dropped off to serve. The vehicle goes to patient 9 only with caregiver_1. After the vehicle drops off caregiver_1 at patient 9, it goes back to patient 7 (dummy node 18) to pick up caregiver_2 empty. After caregiver_2 serves patients 3 and 10 respectively, the vehicle with caregiver_2 goes back to patient 9 (dummy node 20) to pick up caregiver_1. Last, before the vehicle goes back to the HHC center with both caregivers, it visits patient 5 who requested caregiver_2. A similar route could also be seen for vehicle 2 on the right diagram in Figure 3.1.

Table 3.2 lists the parameters and decision variables that we define to formulate the mixed-integer linear programming model of the HHSRP-VS given below.

**Table 3.2.** Model parameters and decision variables

| **Parameters** | **Definition** |
|---|---|
| $t_{ij}$ | Nonnegative and deterministic travel time between nodes $i$ and $j$, $(i,j) \in A$ |
| $d_{is}$ | 1, if patient $i \in V_1$ needs to be treated for illness $s \in S$; 0, otherwise (patients' demands) |
| $q_{ls}$ | 1, if caregiver $l \in L$ is qualified to treat illness $s \in S$; 0, otherwise (caregivers' qualifications) |
| $p_{is}$ | Deterministic service time for treating illness $s \in S$ of patient $i \in V_1$ |
| $c$ | Maximum number of workers allowed to be transferred by a vehicle in addition to the dedicated driver to the vehicle |
| $wTime$ | Maximum daily working time (hour) of caregivers |
| $unv$ | Penalty cost incurred if a patient is not visited |
| $M_1, M_2$ | Big numbers |
| **Variables** | **Definition** |
| $x_{i,j,k}$ | 1, if vehicle k ∈ K travels through node $i \in V$ to node $j \in V$; 0, otherwise. |
| $z_{i,j,k,l}$ | 1, if caregiver $l \in L$ travels through node $i \in V$ to node $j \in V$ with vehicle $k \in K$; 0, otherwise. |
| $y_{i,k,l}$ | 1, if vehicle $k \in K$ drops caregiver $l \in L$ off at node $i \in V_1$ such that the caregiver should be picked up at node $i+n$; 0, otherwise |
| $\alpha_{i,k,l,s}$ | 1, if caregiver $l \in L$ visits patient $i \in V_1$ with vehicle k ∈ K to treat illness $s \in S$; 0, otherwise |
| $u_i$ | 1, if patient node $i \in V_1$ is not visited; 0, otherwise. |
| $hw_{i,l}$ | Waiting time of caregiver $l \in L$ at node $i \in V$ |
| $w_{i,k}$ | Waiting time of vehicle $k \in K$ in node $i \in V$ |
| $av_{i,k}$ | Arrival time of vehicle $k \in K$ to node $i \in V$ |
| $ah_{i,l}$ | Arrival time of caregiver $l \in L$ to node $i \in V$ |
| $dv_{i,k}$ | Departure time of vehicle $k \in K$ from node $i \in$ V |
| $dh_{i,l}$ | Departure time of caregiver $l \in L$ from node $i \in$ V |

**Table 3.2.** Model parameters and decision variables (cont.)

| Auxiliary Variables | Definition |
|---|---|
| $\psi_{i,k,l}$ | 1, if vehicle $k \in K$ visits patient $i \in V_1$ with caregiver $l \in L$ and the caregiver $l$ is not dropped off at the patient (either serves the patient or waits for the assigned caregiver in the vehicle).<br>0, if either vehicle $k$ visits patient $i$ but does not wait for the service by caregiver $l$ (dropped off) or it never visits $i$, |
| $\gamma_{i,k,l}$ | 1, if caregiver $l \in L$ is assigned to vehicle $k \in K$ and patient $i \in V_1$ for serving the patients' illness $s \in S$ and the caregiver $l$ is not dropped off at the patient (the vehicle waits for the service completion),<br>0, if either caregiver $l$ is assigned but dropped off by the vehicle $k$ or caregiver $l$ is not assigned to patient $i$. |

The HHSRP-VS consists of determining a set of $\bar{k}$ routes of the minimal working time of the caregivers to serve the patients by dropping the caregiver off at the patient's home if needed and picking up from the same place by the same vehicle under the working time window of the caregivers, capacity constraints and the following assumptions:

- Each vehicle consists of a fixed number of caregivers.
- There is a single HHC center where vehicles and caregivers start and end their travel.
- The skills of the available caregivers are eligible to meet patients' requirements.
- Each patient requires only one type of service (treatment). Hence a patient is allowed to be visited by a single caregiver and a vehicle for the treatment.
- Every available vehicle and caregiver is required to be utilized.
- If any of the caregivers need to be dropped at any of his/her assigned patient's home for the treatment, he/she must be picked up from the same patient's home by the same vehicle before either return to the depot or visiting the next patient who requested the same caregiver.
- Caregivers are not allowed to work over-time.

The mixed-integer linear programming model of the HHSRP-VS given below.

The objective function minimizes the total flow times of the caregivers until returning to the HHC center, which includes their service, travel and waiting times, and the total penalty cost of unvisited patients, if exist.

$$\min \sum_{l \in L} ah_{(2n+1),l} + \sum_{i \in V_1} u_i * unv \tag{1}$$

Constraint set (2) guarantees that each patient node is visited exactly once or unvisited.

$$\sum_{i \in V} \sum_{k \in K} x_{i,j,k} + u_j = 1 \qquad j \in V_1 \tag{2}$$

Constraint sets (3) and (4) ensure that every available vehicle and caregiver must depart from the HHC center. Moreover, a caregiver must leave with a single vehicle.

$$\sum_{j \in V_1} x_{0,j,k} = 1, \qquad k \in K \tag{3}$$

$$\sum_{j \in V_1} \sum_{k \in K} z_{0,j,k,l} = 1, \qquad l \in L \tag{4}$$

Constraint set (5) maintains flow conservation in the network for vehicles.

$$\sum_{j \in V} x_{i,j,k} - \sum_{j \in V} x_{j,i,k} = 0, \qquad i \in V_1 \cup V_2, k \in K \tag{5}$$

Constraint set (6) aims to relate the travel of vehicles with caregivers. Hence, a caregiver can travel from nodes $i$ to $j$ if his/her assigned vehicle goes that route. Constraint (7) assures that only a single and qualified caregiver is assigned to treat the illness of a patient if being served. Constraint set (8) ensures that the vehicle must visit a patient if the assigned caregiver to the patient is also assigned to that vehicle.

$$z_{i,j,k,l} \le x_{i,j,k}, \qquad i,j \in V, k \in K, l \in L \tag{6}$$

$$\sum_{l \in L} \sum\nolimits_{k \in K} \alpha_{i,k,l,s} * q_{l,s} + u_i = d_{i,s}, \qquad i \in V_1, s \in S \tag{7}$$

$$\sum_{i \in V} z_{i,j,k,l} \ge \sum\nolimits_{s \in S} \alpha_{i,k,l,s}, \qquad j \in V_1, k \in K, l \in L \tag{8}$$

Constraint set (9) maintains that a caregiver could be dropped off at the patient node if the assigned vehicle visits that node. Next, constraint set (10) ensures that the vehicle must visit the patient's dummy node if a caregiver was dropped off at the patient node. Although the terms $y_{j,k,l}$ in (9) and (10) could be replaced by $\sum_{l\in L} y_{j,k,l}$, they might be preferred due to computational sakes (tighter constraints).

$$y_{j,k,l} \leq \sum_{i\in V} x_{i,j,k}, \qquad j \in V_1, k \in K, l \in L \qquad (9)$$

$$\sum_{i\in V} x_{i,(j+n),k} \geq y_{j,k,l}, \qquad j \in V_1, k \in K, l \in L \qquad (10)$$

Constraint set (11) guarantees that the dummy node cannot be visited if none of the caregivers were dropped at the patient. Constraint set (12) ensures that when a caregiver is dropped off at a patient node, that caregiver is not allowed to leave the same patient node, instead, the caregiver must leave from its dummy node due to the two-layer approach.

$$\textstyle\sum_{i\in V} x_{i,(j+n),k} \leq \sum_{l\in L} y_{j,k,l}, \qquad j \in V_1, k \in K \qquad (11)$$

$$\textstyle\sum_{j\in V} \sum_{k\in K} z_{i,j,k,l} \leq 1 - \sum_{k\in K} y_{i,k,l}, \qquad i \in V_1, l \in L \qquad (12)$$

For the sake of the caregivers' flow conservation in the network, constraint sets (13) and (14) guarantee that if a caregiver goes to a patient node, that caregiver must depart from either the same patient node or its dummy node only with the initially assigned vehicle.

$$\sum_{j\in V} z_{j,i,k,l} = \sum_{j\in V} z_{i,j,k,l} + y_{i,k,l}, \qquad i \in V_1, k \in K, l \in L \qquad (13)$$

$$\sum_{j\in V} z_{j,i,k,l} + y_{(i-n),k,l} = \sum_{j\in V} z_{i,j,k,l}, \qquad i \in V_2, k \in K, l \in L \qquad (14)$$

Constraint sets (15) through (28) are required to track the arrival, departure, and waiting times of both caregivers and vehicles. Because both caregivers and vehicles can take different actions throughout the route, their synchronization should be maintained for the accuracy of the flow. Therefore, a vehicle or a caregiver may have to wait for the other for the continuity of the travel. These waiting times could either appear at the first (original patient node) or the second layer (dummy node). These could be briefly explained as in the following.

Constraints (15) and (16) computes the arrival time of vehicles and caregivers to the nodes, respectively. A vehicle could wait at the patient node $i \in V_1$ (first layer) if and only if the vehicle decides to wait for the caregiver until the completion of the service at the patient. The duration of the waiting time is the amount of service time for the patients' requirements (constraint (17)).

$$av_{j,k} \geq dv_{i,k} + t_{i,j} - \left(1 - x_{i,j,k}\right) * M_1, \qquad i,j \in V, k \in K \qquad (15)$$

$$ah_{j,l} \geq dh_{i,l} + t_{i,j} - \left(1 - z_{i,j,k,l}\right) * M_1, \qquad i,j \in V, k \in K, l \in L \qquad (16)$$

$$w_{i,k} \geq \sum_{s \in S} \sum_{l \in L} \gamma_{i,k,l} * p_{i,s} - \sum_{j \in V} x_{j,(i+n),k} * M_2, \qquad i \in V_1, k \in K \qquad (17)$$

A vehicle could wait at the dummy node $i \in V_2$ (second layer) when the vehicle returns to the patient node to pick up the dropped-off caregiver and the caregiver has not completed the service yet. The duration of the waiting time is the difference between the completion time of the caregivers' service and the arrival time of the vehicle to the dummy node (constraint (18)).

$$w_{i,k} \geq av_{(i-n),k} + \sum_{s \in S} \sum_{l \in L} \alpha_{(i-n),k,l,s} * p_{(i-n),s} - av_{i,k} - \left(1 - \sum_{j \in V} x_{j,i,k}\right) * M_1,$$

$$i \in V_2, k \in K \qquad (18)$$

A caregiver in a vehicle, if there is, could wait at the patient node $i \in V_1$ while the assigned caregiver serves the patient, and the vehicle waits for the completion of the service. The duration of the waiting time is equal to the amount of service time at the patient (constraint (19)).

$$hw_{i,l} \geq \sum_{s \in S} \sum_{l' \in L \setminus \{l\}} \gamma_{i,k,l'} * p_{i,s} - \left(1 - \sum_{k \in K} \psi_{i,k,l}\right) * M_2, \qquad i \in V_1, l \in L \qquad (19)$$

The assigned caregiver could wait at the dummy node $i \in V_2$ if the vehicle returns later than the caregivers' service completion. The waiting time is the difference between the arrival time of the vehicle to the patient and the completion time of the caregivers' service (constraint (20)).

$$hw_{i,l} \geq av_{i,k} - \sum_{s \in S} \sum_{l' \in L} \alpha_{(i-n),k,l',s} * p_{(i-n),s} - av_{(i-n),k} - \left(1 - y_{(i-n),k,l}\right) * M_1,$$

$$i \in V_2, k \in K, l \in L \qquad (20)$$

Constraint sets (21) and (22) determines the departure time of vehicles and caregivers from the nodes, respectively. A caregiver could also wait at the dummy node $i \in V_2$, if he/she returns to the patient with the vehicle to pick up the dropped-off caregiver earlier than the assigned caregivers' service completion. This waiting time was not explicitly computed because it is handled by both constraint (20) and the synchronization constraints (23)-(26). The synchronization constraints (23) through (26) aim to synchronize the arrival and departures of a vehicle and the caregivers within it throughout the nodes.

$$dv_{i,k} \geq av_{i,k} + w_{i,k}, \qquad i \in V, k \in K \qquad (21)$$

$$dh_{i,l} \geq ah_{i,l} + hw_{i,l}, \qquad i \in V, l \in L \qquad (22)$$

$$av_{i,k} + \left(1 - \sum_{i \in V} z_{j,i,k,l}\right) * M_1 \geq ah_{i,l}, \qquad i \in V, k \in K, l \in L \qquad (23)$$

$$av_{i,k} \leq ah_{i,l} + \left(1 - \sum_{i \in V} z_{j,i,k,l}\right) * M_1, \qquad i \in V, k \in K, l \in L \qquad (24)$$

$$dv_{i,k} + \left(1 - \sum_{j \in V} z_{i,j,k,l}\right) * M_1 \geq dh_{i,l}, \qquad i \in V, k \in K, l \in L \qquad (25)$$

$$dv_{i,k} \leq dh_{i,l} + \left(1 - \sum_{j \in V} z_{i,j,k,l}\right) * M_1, \qquad i \in V, k \in K, l \in L \qquad (26)$$

Constraints (27) and (28) are used to indicate whether a vehicle takes a caregiver to a patient and waits for the service and whether the assigned caregiver to a patient is not dropped off by the vehicle, respectively (see Table 3.2 for the description of the respective auxiliary variables).

$$\psi_{i,k,l} = \sum_{j \in V} z_{j,i,k,l} - y_{i,k,l}, \qquad i \in V_1, k \in K , l \in L \qquad (27)$$

$$\gamma_{i,k,l} = \sum\nolimits_{s \in S} \alpha_{i,k,l,s} - y_{i,k,l}, \qquad i \in V_1, k \in K, l \in L \qquad (28)$$

Constraint (29) ensures the capacity of vehicles in terms of the number of caregivers.

$$\sum_{j \in V_1} \sum_{l \in L} z_{0,j,k,l} = c, \qquad k \in K \qquad (29)$$

Constraints (30) and (31) specifies the maximum working time of caregivers and vehicles. Even though one of the constraints (30) or (31) is enough, we embedded both to tighten the model. For the same concern, $M_1$ and $M_2$ could be replaced with tighter $wTime$ and $\sum_{i \in V_1} \sum_{s \in S} p_{i,s}$ values, respectively.

$$ah_{(2n+1),l} \leq wTime, \qquad l \in L \qquad (30)$$

$$av_{(2n+1),k} \leq wTime, \qquad k \in K \qquad (31)$$

Finally, constraint set (32) shows the feasible values of decision variables.

$$\begin{gathered} x_{i,j,k}; z_{i,j,k,l}; y_{i,k,l}; \alpha_{i,k,l,s}; u_i; \psi_{i,k,l}; \gamma_{i,k,l} \in \{0,1\}, \\ hw_{i,l};\ w_{i,k};\ av_{i,k};\ ah_{i,l};\ dv_{i,k};\ dh_{i,l} \geq 0 \end{gathered} \qquad (32)$$

On an individual basis, the complexity of WSRP (Algethami et al., 2019) and VPSP (Bei and Zhang, 2018) are both NP-Hard. As seen in the mathematical model, HHSRP-VS can be reduced into WSRP by setting dummy set to empty set such as, $V_2 = \emptyset$. The dummy set and the constraints associated with this set introduce additional decisions into the model and enlarges the solution space which significantly increases the complexity of it. Thus, we can conclude that HHSRP-VS is as difficult as WSRP. The following sections explain the attempts to tighten the model by finding an upper bound and obtain close-optimal solutions using a metaheuristic algorithm.

## 3.3. Upper Bound Heuristic (UBA): A Clustering-Based Matheuristic Approach

In literature, various HHSRP problems were solved by decomposition-based algorithms in two stages in which the patients are either clustered or partitioned based on caregivers' skills, geographical proximity, or some other characteristics at the first stage. Next, the reduced problem is solved as a variant of Traveling Salesman Problem (TSP) or VRP using MILP or heuristics (Rasmussen et al., 2012, Hiermann et al., 2015, and Erdem and Bulkan, 2017). A multi-stage decomposition-based matheuristic algorithm is developed to find feasible solutions.

In the first stage, the caregiver clusters are formed based on the geographical closeness of the patients similar to the K-means clustering algorithm. The basic principle of this clustering is that the patients with the shortest distance from the centroid of the cluster should be placed under the same cluster. For the problem under consideration, the clusters have been formed based on the caregivers' skills and qualifications and the patients' demands and their locations. As a solution to the clustering problem, the caregiver is at the centroid of the clusters which is a midpoint of all the assigned patients' points of the respective cluster. In this clustering, patients are assigned in such a way that the demand of every patient should be matched to the caregiver's skill(s).

***input:*** *Service time of patients* $p_{is}$, *sets of patients* $V_1$ *and caregivers* $L$, *coordinates of patients* $p_i$
***output:*** $H_l$: *caregiver cluster,* $c_{hl}$: *the centroid of* $H_l$, *respectively.*

1 **Start Stage 1: Initialize caregiver clusters:**
**forall** *caregivers* $l \in L$
  **Assign** *patient* $i \in \widehat{V}_1$ *where* $\widehat{V}_1 \leftarrow V_1$ *to cluster* $H_l$ *if*
   - *patient* $i$ *can be treated by caregiver* $l$ *and the distance between* $p_i$ *and HHC center is the maximum*

  **Update** $\widehat{V}_1 \leftarrow \widehat{V}_1 \backslash \{i\}$, $H_l = \{i\}$, $ch_l = p_i$.
***If*** $H_{l'} = \emptyset$, $l' \in L$ *then* **forall** *caregivers* $l'$
  **Find** *a proper patient* $i$ *from the created clusters* $H_l$, **Remove** *it from that cluster and* **Assign** *it to* $H_{l'}$.
  **Assign** *the furthest patient* $i \in \widehat{V}_1$ *that can be treated by caregiver* $l$ *to* $H_l$
  **Update** $H_{l'} = \{i\}$, $ch_{l'} = p_i$, $H_l = \{i'\}$, $ch_l = p_{i'}$, $\widehat{V}_1 \leftarrow \widehat{V}_1 \backslash \{i'\}$

2 **Complete and Improve clusters (K-means algorithm with qualification constraint)**
**Repeat forall** *patient* $i \in V_1$
  **forall** *caregiver clusters* $l \in L$ *such that* $H_l \cap \{i\} = \emptyset$
   **Find** *the nearest cluster* $H_l$ *where caregiver* $l$ *can treat patient* $i$. *If there is no such a cluster,* **Move** *to the next patient. Otherwise;*
   **Remove** *patient* $i$ *from its clusters* $H_{l'}$ *and* **Add** *it to* $H_l$.
   **Update** $H_{l'} \leftarrow H_{l'} \backslash \{i\}$, $H_l \leftarrow H_l \cup \{i\}$, $ch_l = \frac{\sum_{i \in H_l} p_i}{|H_l|}$, $l \in L$
**until** *there is no further improvement*

3 **Recluster patients to balance total service workload**
**Compute** *the maximum total service time allowed per worker:* $\overline{ts} = \sum_{i \in V_1} \sum_{s \in S} \frac{p_{is}}{l} + \max_{i \in V_1, s \in S} p_{is}$
  **forall** *caregiver clusters* $H_l, l \in L$
   **If** *total workload in cluster* $l$ *exceeds the maximum allowance:* $ts_l > \overline{ts}$ *such that* $ts_l = \sum_{i \in H_l} \sum_{s \in S} \frac{p_{is}}{|H_l|}$.
   **Remove** *the furthest patient* $i'$ *in cluster* $H_l$ **until** $ts_l \leq \overline{ts}$. **Assign** *patient* $i'$ *to a candidate list* $CL$.
   **Update** $H_l \leftarrow H_l \backslash \{i'\}$, $CL \leftarrow CL \cup \{i'\}$, $ch_l = \frac{\sum_{i \in H_l} p_i}{|H_l|}$, $l \in L$
  **forall** *patient* $i \in CL$
   **Find** *the nearest cluster* $H_l$ *where caregiver* $l$ *can treat patient* $i$ *and* $ts_l + p_{is} \leq \overline{ts}$. *Then* **Assign** *patient* $i$ *to* $H_l$.
   **Update** $H_l \leftarrow H_l \cup \{i\}$, $CL \leftarrow CL \backslash \{i'\}$, $ch_l = \frac{\sum_{i \in H_l} p_i}{|H_l|}$, $l \in L$, $ts_l = ts_l + p_{is}$
  **If** $CL \neq \emptyset$, **Repeat**
   **Assign** *patient* $i \in CL$ *to the nearest* $H_l$ *where caregiver* $l$ *can treat patient* $i$ *even if total workload exceeds* $\overline{ts}$
   **Update** $H_l \leftarrow H_l \cup \{i\}$, $CL \leftarrow CL \backslash \{i'\}$, $ch_l = \frac{\sum_{i \in H_l} p_i}{|H_l|}$, $l \in L$, $ts_l = ts_l + p_{is}$
  **Until** $CL = \emptyset$
**STOP**

**Figure 3.2.** The pseudocode of the first stage of the proposed UBA

This solution is feasible for HHSRP-VS for the following reasons. (a) All caregivers have been utilized. (b) Qualification constraint is satisfied. Furthermore, to deal with working time constraints, the algorithm aims to evenly distribute the total service workload of each caregiver. The detailed pseudocode of the first stage of the proposed algorithm can be seen in Figure 3.2.

In the second stage, caregiver clusters are assigned to vehicles according to the capacity of vehicles. The idea behind this caregivers-vehicle assignment is that the caregivers can visit their patients through the same vehicle who are living close to each other. So, in this stage, the caregiver clusters which are closer to each other are assigned to the same vehicle. As a result of the second stage, we determine which caregivers are assigned to which vehicle and which patients are going to be treated by which caregiver.

***input:*** *Caregiver clusters* $H_l$ *and its centroid* $ch_l$ *from Algorithm 1. Set of vehicles* $K$*, maximum daily working time* $wTime$*, penalty cost patient* $unv$*, capacity of vehicle* $c$*.*
***output:*** $A_k$ *and* $cv_k$ *that indicate the vehicle cluster and its centroid, respectively.* $H_l$ *is the visited patient list by caregiver* $l$*,* $u$ *is the unvisited patient list,* $z_k$ *is the tour length of vehicle* $k$*,* $\mu$ *is the total fitness value of the solution,* $\pi_k$ *is the route of vehicle* $k$*,.*

---

5 **Start Stage 2: Create vehicle clusters:**

**Assign** *the furthest caregiver cluster* $H_l$ *from the HHC center to the first vehicle cluster.*

**Update** $A_1 \leftarrow A_1 + \{H_{l'}\}$, $cv_1 = ch_{l'}$, $H_l$, $L' \leftarrow L \backslash \{l'\}$.

**forall** *vehicle cluster* $k \in \frac{K}{\{1\}}$

  **Assign** *the furthest caregiver cluster* $H_l$, $l \in L'$ *from the centroid of the previously initialized vehicle clusters* $j = 1, \dots, k-1$ *to the vehicle cluster.*

  **Update** $A_k \leftarrow A_k + \{H_{l'}\}$, $cv_k = ch_{l'}$, $L' \leftarrow \frac{L'}{\{l'\}}$

**forall** *caregiver clusters* $H_l, l \in L'$

  **Assign** *the nearest* $H_l$ *to vehicle cluster* $A_k$ *such that the capacity of vehicle* $k$ *is not exceeded such that* $|A_k| \leq c$

  **Update** $A_k \leftarrow A_k + \{H_l\}$, $cv_k = \frac{\sum_{i \in H_l \in A_k} p_i}{\sum_{H_l \in A_k} |H_l|}$, $L' \leftarrow L \backslash \{l'\}$

---

**STOP**

---

**Figure 3.3.** The pseudocode of the second of the proposed UBA

In the third stage, the problem is turned into a multiple TSP where the optimal route of each vehicle is computed sequentially using the IBM ILOG CPLEX 12.6 solver without considering the maximum working time constraints. After the optimal route of the first vehicle is obtained, if the solution exceeds the working time limit, the costliest patients on the route are removed until the working time constraint is maintained. The removed patients of the vehicle are added to the patient list of the next qualifying vehicle. After solving the last vehicle, if there are still removed patients, they are considered as the unvisited patients. The detailed pseudocode of the second and third stages of the proposed algorithm can be seen in Figure 3.3 and Figure 3.4, respectively.

---

6 **Start Stage 3: Construct the optimal routes of the vehicles**
**forall** *vehicle cluster* $k \in K$
  **Solve** *the respective TSP using IBM ILOG CPLEX 12.6 to obtain the optimal route,* $\pi_k$*, of* $A_k$
  *If* $z_k > wTime$
    **Repeat forall** *patient* $i \in A_k$
    **Compute** *the costliest patient* $i$ *considering its contribution to* $z_k$ *as similar to Clarke and Wright's savings algorithm. Let the cost of patient* $i$ *be* $d_i$*.*
    **Remove** *patient* $i$ *and*
      **If** $k \neq |K|$
        **Assign** *it to the* $A_{k+1}$*, patient list of vehicle* $k+1$*.*
      **Else**
        **Assign** *it to the unvisited patient list* $u$*.*
    **Update** $A_k \leftarrow A_k \backslash \{i\}$, $u \leftarrow u \cup \{i\}$, $z_k = z_k - d_i - p_i$, $cv_k = \frac{\sum_{i \in A_k} p_i}{|A_k|}$,
    **Until** $z_k \leq wTime$

---

**STOP**

---

**Figure 3.4.** The pseudocode of the third stage of the proposed UBA

In the final stage, we applied an inter-route relocate operator to look for better solutions and a repair function to reduce the unvisited number of patients at the end. Since the optimal route of each vehicle is obtained in the previous stage, changing a patient's position on the same route does not improve the solution. Thus, the inter-route relocate operator removes a patient from its vehicle and inserts it in another qualifying vehicle. The feasibility of the solution is conserved at each iteration by satisfying qualification and maximum working time constraints. Finally, a repair function with a greedy heuristic is applied to assign the unvisited patients to vehicles whose total working time is less than the maximum working time. The pseudocode of the inter-route relocate operator and repair function can be seen in Figure 3.5.

In order to narrow the solution space and obtain feasible integer solutions in a short time, we used the solution ($\mu$) obtained by the proposed mathematical algorithm as the upper bound for the original mathematical model of HHSRP-VS. This solution can be used as an upper bound because it does not include the drop-off and pick-up policy but satisfies all other constraints. For this purpose, equations (33) and (34) can be added as valid upper bound inequalities to the HHSRP-VS MILP model. Moreover, we also used solutions provided by the upper-bound algorithm to analyze the effectiveness of the ALNS-VS algorithm developed in the following sections.

$$\sum_{k\in K} av_{(2n+1),k} + \sum_{i\in V_1} u_i * unv \leq \mu, \tag{33}$$

$$\sum_{l\in L} ah_{(2n+1),l} + \sum_{i\in V_1} u_i * unv \leq \mu, \tag{34}$$

---

***input:*** *Set of vehicles* $K$, *Route of vehicles* $\pi_k = \{v_0, v_1, \dots, v_i, \dots, v_{2n+1}\}$, , $t_{i,j}$ *travel time between node* $i$ *and* $j$, $\delta_{i,j}^{k_1,k_2}$ *relocate value of assigning patient* $v_i$ *from vehicle* $k_1$ *to position* $j$ *of vehicle* $k_2$, $u$ *is the unvisited patient list, penalty cost of unvisited patient* $unv$

***output*** $z_k$ *is the tour length of vehicle* $k$, $\pi_k$ *is the route of vehicle* $k$, $\mu$ *is the total fitness value of the solution.*

---

7 **Feedback Loop:**

**Do**

  **forall** *vehicle* $k_1 \in K$

    **forall** *position* $i \in \pi_{k_1}$ *such that* $v_i$ *is the patient of position* $i$

      **forall** *vehicle* $k_2 \in K \backslash \{k_1\}$

        **forall** *feasible positions* $j \in \pi_{k_2}$

          **Compute** *the relocate value* $\delta_{i,j}^{k_1,k_2}$ *such that,*

$$\delta_{i,j}^{k_1,k_2} = t_{v_{i-1},v_i} + t_{v_i,v_{i+1}} + t_{v_{j-1},v_j} - \left(t_{v_{j-1},v_i} + t_{v_{j-1},v_i}\right)$$

        **end for**

      **end for**

    **end for**

  **end for**

  **Determine** $\delta_{i^*,j^*}^{k_1^*,k_2^*} = \max_{i,j,k_1,k_2} \left\{\delta_{i,j}^{k_1,k_2}\right\}$

  **If** $\delta_{i^*,j^*}^{k_1^*,k_2^*} > 0$

      **Remove** *the patient* $v_{i^*}$ *of position* $i$ *from the vehicle* $k_1^*$ *and* **Assign** *it to the position* $j^*$ *of the vehicle* $k_2^*$

      **Update** $z_{k_1^*}$ *and* $z_{k_2^*}$, *tour length of vehicles* $k_1^*$ *and* $k_2^*$, *respectively*

**While** $\delta_{i^*,j^*}^{k_1^*,k_2^*} > 0$

---

**STOP**

---

8 **Repair Function:**

**While** $u \neq \emptyset$ **and** *there is any feasible assignment*

  **forall** *unvisited patient* $v_i \in u$

    **forall** *route of vehicle* $\pi_k \in K$

      **forall** *feasible position* $j \in \pi_k$

        **Compute** *the insertion cost of patient* $v_i$ *into position* $j$ *of vehicle* $\pi_k$

      **end for**

    **end for**

  **end for**

  **Insert** *the patient into the determined position of the vehicle that has minimum insertion cost*

  **Update** $\pi_k \in K, z_k \in K, u$

**end while**

**Compute** *total service and travel time of the visited patients and the penalty cost for unvisited patients* $\mu$:

$\mu = \sum_k z_k + \sum_{l\in L} \sum_{i\in H_l} \sum_{s\in S} p_{is} + \sum_{i\in u_i} unv$

---

**Figure 3.5.** The pseudocode of the feedback loop and repair function of the proposed UBA

# CHAPTER 4

# SOLUTION METHODOLOGY: ALNS-VS Algorithm

Because of the complexity of the problem, decomposition-based algorithms or metaheuristics are commonly used solution algorithms to solve HHSRP in the literature. This chapter presents the developed Adaptive Large Neighborhood Search (ALNS) heuristic algorithm for solving HHSRP-VS. The ALNS algorithm was first proposed by Ropke and Pisinger (2006a) by extending Large Neighborhood Search (LNS) algorithm proposed by Shaw (1997). Unlike the LNS, the ALNS heuristic involves a variety of removal and insertion heuristics which help in obtaining a good quality solution. As far as the other heuristics are concerned, ALNS is relatively fast and has been successfully implemented in different variants of VRP. Therefore, we preferred to adapt the ALNS for our problem. To deal with the DP policy of the problem under study, two local search heuristics have been introduced within the proposed ALNS-VS algorithm of which its details are discussed below.

The algorithm in our study starts with finding an initial solution after which in every iteration it randomly selects a removal heuristic to deconstruct the existing solution to some extent and an insertion heuristic to repair it differently. Through this destroy and repair operations, a new neighborhood solution is obtained at the end of each iteration and is adopted as the current solution for the next iteration. These the processes continue until the stopping criteria are met. The pseudocode of the proposed ALNS-VS is presented in Figure 4.1. The details of the algorithm with the parameter definitions are explained in the following subsections.

## 4.1. Initial Solution

At the beginning of the ALNS-VS algorithm, all of the patient nodes are placed in the request bank $R$ and all of the dummy nodes are placed in the dummy request bank $\bar{R}$. Caregivers are assigned to vehicles at random until the capacity of each vehicle is filled. At each successive step the *Regret-3 heuristic with noise* algorithm (see Chapter 4.3) is applied to all the vehicles in parallel by assigning each patient $i \in V_1$ from $R$ to one of the existing fleet vehicles. This process is repeated until all patients are assigned to one of the available vehicles $k \in K$ or remaining patients cannot be assigned to any vehicle due to maximum working time of caregivers. Once a feasible solution is found, it is set to the current solution and the best solution.

```
input: The set of removal heuristics Ψ, the set of insertion
heuristics Z, initial temperature T, cooling rate c, solution
update iteration number ω, caregiver swap iteration number φ,
the iteration of the last best-found solution t_best
output: A feasible solution x_best
---------------------------------------------------------------
Generate an initial solution x_init using the Regret-3 with noise
insertion heuristic
Set iteration counter t with an initial value of t ← 1 and
t_best ← 1
Set the initial values, x_curr ← x_best ← x_init
repeat
 | if (t − t_best % ω = 0) then
 |    | Apply solution update criteria to x_new
 |    | x_curr ← x_best
 |    |_ Ψ* ← Random.Removal
 | else
 |       |_ Select a removal heuristic at random, Ψ* ∈ Ψ
 | Let x_new be a partial solution after applying Ψ* to x_curr
 | if (t % φ = 0) then
 |   |_ Apply caregiver swap local search heuristic to x_new
 | Select a random insertion heuristic Z* ∈ Z to x_new to generate
 | x_new
 | Let x_new be a new solution after applying Z* to x_new
 | Apply drop-off and pick-up local search heuristic to improve
 | x_new
 | Apply repair function to generate a new feasible solution
 | x_new and determine the unvisited patients
 | if f(x_new) < f(x_curr) then
 |       | x_curr ← x_new
 |       |_ f(x_curr) ← f(x_new)
 | else
 |       | Let v ← e^(−(f(x_new)−f(x_curr))/T)
 |       | Generate a random number ϵ ϵ [0,1]
 |       | if ϵ < v then
 |       |   | x_curr ← x_new
 |       |___|_ f(x_curr) ← f(x_new)
 | if f(x_new) < f(x_best) then
 |   | x_best ← x_new
 |   |_ f(x_best) ← f(x_new)
 | Update the temperature, T ← c * T
 | Update the iteration counter, t ← t + 1
until the predetermined number of iterations reached and the
predetermined number of iterations without any further
improvement found in x_best
```

**Figure 4.1.** Pseudocode of the proposed ALNS-VS

## 4.2. Removal Heuristics

At each iteration, a randomly selected removal heuristic algorithm removes a predetermined number of patients $q$ from the current solution $x_{curr}$ and places them to the request bank *R*. In general, $q$ is set to an integer number at the beginning of the algorithm in the literature (Ropke and Pisinger, 2006a, 2006b; Pisinger and Ropke, 2007). However, varying $q$ may be preferred due to exploration and explotation capabilities of the heuristics. For this, linearly decreasing function of $q$ is used in our algorithm to explore the solution space more at the beginning of the iterations than the later (Öztürkoğlu et al., 2014; Öztürkoğlu and Hoser, 2019). At each iteration, the number of removed patients $q$ is computed using equation (35).

$$q = \xi * n - n * (\xi - \upsilon)\frac{t}{\theta} \tag{35}$$

where, $n$ is the total number of patients, $\xi$ and υ are the parameters that control the maximum and minimum number of removed patients, $t$ is the current iteration and $\theta$ is the maximum number of iterations. As Pisinger and Ropke (2007) suggested that the minimum number of removed elements from a solution should be $10\%$ ($\upsilon = 0.1$) of the total number of elements. Furthermore, we adapted 5 different removal heuristics in our proposed ALNS-VS algorithm, which are explained below.

**Random Removal:** This heuristic algorithm randomly removes $q$ patients from the current solution $x_{curr}$ and adding them to the request bank R.

**Worst Removal:** This heuristic algorithm selects $q$ costliest patients in terms of distance from the current solution. The heuristic removes the selected patient $i \in x_{curr}$ from the current solution $x_{curr}$ and adds them to $R$. After removing patient $i$, the cost of the $x_{curr}$ is calculated as $f_{-i}$, whereas the cost of $i$ can be calculated as $\Delta f_i = f(x_{curr}) - f_{-i}$.

**Shaw Removal:** The main objective of this heuristic algorithm is to remove the most similar patients in terms of their locations and service times. The heuristic starts with selecting a random patient $i \in x_{curr}$ and adding it to the request bank $R$. The similarity measures ($d_{ij}$) between the selected patient $i$ and the rest of the patients $j \in x_{curr} \backslash \{i\}$ in the solution $x_{curr}$ are calculated by $d_{ij} = \alpha * t_{i,j} + \beta * (|p_i - p_j|)$. In our problem, the lower the $d_{ij}$ is the higher the similarity. The most similar patient $j^*$ is selected and added to $R$ such that $j^* = argmin_{j \in x_{curr}} d_{ij}$, where $\alpha$ and $\beta$ are the shaw parameters, $p_i$ and $p_j$ are the service times of patients $i$ and $j$, and $t_{i,j}$ is the travel time between patient nodes $i$ and $j$. This heuristic algorithm is iteratively applied $q$ times to determine the removed patients such that the patient has the maximum similarity measure with the last removed patient.

**Route Removal:** This heuristic algorithm randomly selects a route of a vehicle $\underline{v}$ from $v$ (a set of routes of vehicles in $x_{curr}$), removes all the patients from it, and adds them to the $R$. The idea of route removal is to redesign the route to minimize the travel time by diversifying the search.

**Dummy Node Removal:** Within the scope of the drop-off and pick-up policy, patients' dummy nodes are also included in the $x_{curr}$. This heuristic algorithm removed $q$ dummy nodes, where $q$ is a random integer number between $\sigma * d$ and $\phi * d$. $d$ is the total number of dummy nodes in the current solution. $\sigma$ and $\phi$ are the minimum and maximum ratios of the dummy removal constant, respectively. Since the drop-off and pick-up local search algorithm is applied at each iteration, removing a large number of dummy nodes from the solution helps to explore different solutions. Therefore, $\sigma$ and $\phi$ are set to 0.5 and 0.8, respectively. Finally, the removed dummy nodes are added to dummy request bank $\underline{R}$.

## 4.3. Insertion Heuristics

In the literature, insertion heuristics are generally categorized as sequential and parallel algorithms. Sequential insertion heuristic algorithms select one vehicle at a time and then construct its route by adding patients. On the other hand, parallel insertion heuristic algorithms consider all the vehicles' routes simultaneously. For our study, we implemented parallel heuristics due to their expected ability to generate superior solutions compared to sequential heuristics, even though sequential insertions are faster (Liu and Shen, 1999). Greedy and Regret-k insertion heuristics were used in the proposed algorithm. In addition to those heuristics, their noise versions were also considered (Ropke and Pisinger, 2006a, 2006b). These heuristics enables the assignment of non-assigned patients from the request bank ($R$) to existing route of vehicles if it could improve the objective function value of the solution.

**Greedy Insertion:** All of the patients from $R$ are assigned to all possible positions of the routes $v$ of caregivers and an insertion cost is calculated for each position through $\Delta^{l}_{i,k,j}= t_{i,k} + t_{k,j} - t_{i,j}$ for $i, j = 1, \dots, n$ and $i \neq j$. In this process, only feasible assignments are considered. After insertion cost is calculated for all patients, the patient with the least insertion cost is assigned to determine the position of the route of the vehicle. This process continues until all patients are assigned to a route or no more insertion is possible. Since at each iteration only one route of a vehicle is changed, the insertion cost for the other routes does not need to be recalculated. This idea improves the computation time for all of the insertion heuristics.

**Greedy Insertion with Noise:** The idea of adding noise to the insertion cost is to provide randomization to the search process. This is done by considering the degree of freedom in determining the best location for a node. The steps of greedy insertion heuristic remain the same while the new insertion cost is calculated by $\Delta_{i,k,j}^{l} = t_{i,k} + t_{k,j} - t_{i,j} + t_{max} * \mu * \varepsilon,$ where $t_{max}$ is the maximum time between patients, $\mu$ is the noise parameter which is used for the diversification and set to 0.1, and $\varepsilon$ is a random number between [-1,1].

**Regret-k Insertion**: Regret-k heuristics are proposed by Potvin and Rousseau (1993). Contrary to the greedy insertion, this heuristic considers the $k$ best positions (depending on choice) instead of the best one. Patients are assigned to positions to maximize the regret cost ($cost_i^k$) which is computed as the difference between $k$ best position costs $\Delta_{i,m,j}^{l}$, change in objective value by inserting patient $m$ between patients $i$ and $j$ in route $v$. In this respect, the greedy heuristic can be seen as a regret-1 heuristic. The proposed algorithm considers regret-2 and regret-3 insertions.

**Regret-k Insertion with Noise:** The steps of this insertion heuristic are similar to the regret-k insertion heuristics but use the same cost function as discussed in the greedy insertion with noise.

## 4.4. Drop-off and Pick-up (DP) Local Search Heuristic Algorithm

In addition to the removal and insertion heuristics, we developed a special local search heuristic algorithm to determine whether a caregiver should be dropped off or waited by the vehicle at a patient node during his/her service. This local search is applied to the solution obtained after the removal and insertion heuristics are completed. Because of the complexity of the drop-off decision and its effect on the whole tour, we developed a smart approach for deciding drop-off and pick-up. Hence, this approach consists of the following features. The pseudocode of the DP local search heuristic is also given in Figure 4.2.

● The effect of DP on the route length is computed for decision-making.

● The position where the patient is being picked up is determined.

● When more than one caregiver is eligible to treat a patient, the approach also decides the best caregiver who is being dropped off at the patient node (if applied).

● The feasibility of the solution is maintained when DP is decided to be applied. For example, if a caregiver $l$ is decided to be dropped off at patient node $i$ and to be picked up before visiting patient $j$, then the patients between $i+1$ and $j$; $[i+1, j]$ in the existing route are guaranteed to be treated by the other caregivers in the vehicle.

```
input: Route of vehicle π_k, k ∈ K in the x_curr, and the saving of
dropping the caregiver l off at the patient i and picking up
after visiting the node j by vehicle k, dp^l_{i,j,k}
output: A new feasible solution x_new
  for all route of vehicle in π_k, k ∈ K
    do
      for all caregivers l ∈ π^l_k in vehicle k
        for all patients i ∈ π_k
          for all patients j ∈ π_k that are being visited after
          patient i
            drop caregiver l off at patient i, then add
            patient i's dummy node after patient j, and calculate
            dp^l_{i,j,π_k} using equation (36)
          end for
        end for
      end for
      Update π_k with the drop-off and picking-up decision
      where the maximum positive dp^l_{i,j,π_k} occurs if it exists.
      Then, update the current solution.
    while dp^l_{i,j,π_k} > 0
  end for
  return A new improved feasible solution x_new ← x_curr
```

**Figure 4.2.** The framework of the drop-off and pick-up local search heuristic algorithm.

The amount of savings on one caregivers' flow time in a vehicle $dp^l_{i,j,\pi_k}$ is calculated using equation (36). This saving, if exist, is induced by dropping caregiver $l$ off at a patient $i$ and picking up after node $j$ in route $\pi_k$ of vehicle $k$. Note that the notations were previously defined in Table 3.2.

$$dp^{l}_{i,j,\pi_k} = \left(t_{j,(j+1)} + p_{is}\right) - \left(t_{j,(i+n)} + \left(0, av_{ik} + p_{is} - \left(dv_{jk} + t_{j,i+n}\right)\right) + t_{i+n,(j+1)}\right), \tag{36}$$

The first term indicates the maximum amount of savings induced by the elimination of waiting for caregiver $l$ at patient $i$ with a duration of $p_{is}$ and the removal of travel from nodes $j$ to $j+1$ in the existing route because the dummy node $i+n$ must be visited after node $j$. The second term specifies the amount of increase in flow time due to drop-off. Hence, the first and the last terms indicate additional travels from nodes $j$ to $i+n$ and $i+n$ to $j+1$. The second term includes the waiting time of caregiver $l$, who was dropped off at patient $i$, if the vehicle arrives at the dummy node later than the service completion time of the caregiver If the saving is greater than zero, then the drop-off and pick-up decision is made.

Since the decision of drop-off and pick-up caregivers affects the arrival and departure times at nodes, the following algorithm (see Figure 4.3) shows the computation of vehicles' route lengths.

**input:** Routes of vehicles $\pi_k$, $k \in K$ in the $x_{curr}$, where, $\pi_k = \{0, \dots v_{i-1}, v_i, v_{i+1}, \dots, 2n+1\}$, travel time between patient $i$ and $j$, $t_{i,j}$, time of arrival at patient $i$, $av_{ik}$ and service time of patient $i, p_{is}$
**output:** Update $av_{ik}$ in $x_{curr}$.

**for** all route of vehicle, $\pi_k$ in the $x_{curr}, k \in K$
    **for** all nodes $v_i$ in route $\pi_k$
        $av_{v_i,k} = av_{v_{i-1},k} + t_{v_{i-1},v_i}$
        **if** no caregiver is dropped off at node $v_{i-1}$
            $av_{v_i,k} += p_{v_{i-1},s}$
        **end if**
        **if** node $v_i$ is a dummy node
            node $v_{i'}$ represents the original patient node of dummy node $v_i$
            $av_{v_i,k} = \max\left(av_{v_i,k}, a_{v_{i'},k} + p_{v_{i'},s}\right)$
        **end if**
    **end for**
**end for**
**return** Update $x_{curr}$.

**Figure 4.3.** Computation of flow time.

## 4.5. Caregiver Swap Heuristic Algorithm

After the caregivers were randomly assigned to the vehicles in the initial solution, any of the applied insertion or removal heuristics do not change their assignments. To search for the whole solution space and look for better caregiver-vehicle-patient assignments, we proposed the caregiver swap heuristic algorithm. The proposed heuristic was inspired by the pheromone concept used in the Ant Colony Optimization (ACO) algorithm introduced by Colorni et al. (1991), in which pheromone is used to trace the most commonly visited paths to find the food source by ants.

In this heuristic, the pheromone density $\tau_{i,j}(t),\ i,j \in L$ is shared among all the caregivers at iteration $t$. Initially, the pheromone values are equal for all of the caregivers. Then the pheromone density between the caregivers in the same vehicle increases depending on their contributions to the solution. The higher the pheromone density among the caregivers, the more likely they are to be assigned to the same vehicle. In addition to the contribution to the solution, the pheromone density is also affected by the heuristic (visibility) value $\eta_{i,j}\ i,j \in L$. Similar to Öztürkoğlu (2017), the pheromone density for all caregivers that are in the same vehicle is updated by:

$$\tau_{i,j}(t) = (1-\rho) * \tau_{i,j}(t-1) + \rho * \left(\frac{\eta_{i,j}}{f_{best}(t-1)}\right), \qquad (i,j) \in L \qquad (37)$$

where $\rho$ denotes the evaporation coefficient whose values lie between $(0,1)$, and $f_{best}$ is the best objective function value found until iteration $t-1$. Thus, the probability of assigning caregivers into the same vehicle is calculated by:

$$\mathrm{P}_{i,j}(t) = \frac{\tau_{i,j}(t-1)}{\sum_{(k,l)\in L} \tau_{k,l}(t-1)}, \qquad (i,j) \in L \qquad (38)$$

Hence, the tournament selection procedure is performed to determine the other caregiver(s) who share the vehicle with the previously assigned caregivers. This process continues until all the caregivers are assigned to their respective vehicles according to the vehicle capacity.

For the proposed caregiver swap heuristic, we consider two different visibility values $\eta_{i,j}$ based on the common and unique number of patients that can or cannot be treated by caregivers $i$ and $j$. The idea behind common patients is that the possibility of a continuum of treating other patients by a caregiver increases after his/her colleague(s) is dropped off at a patient. Hence, this may efficiently use the DP policy by reducing the number of returns. On the other side, in the case of unique patients, the algorithm may cluster closer patients that have distinct requirements to each other. Hence, the closer distinct patients may increase the chance of using DP policy where a vehicle may go forth and back between them due to drop-off and pick-up. In Chapter 5.3, we investigate if there is any difference between the common and unique visibility heuristics, as well as the effect of caregiver swap heuristic on the quality of the solution.

### 4.6. The Repair Function and Termination Criteria

Through the application of removal and insertion heuristics and DP local search heuristic algorithm, we only consider qualification and demand constraints. The total working time constraint is ignored to explore a high variety of solutions and to speed up the heuristics by avoiding recomputing the flow time after every insertion. Therefore, a repair function is proposed to restore the feasibility of the solutions after all insertion and the DP heuristic are applied. Thus, a new feasible solution is being directed to the next iteration if accepted.

The proposed repair function given in Figure 4.4 guarantees the feasibility of the solutions within two steps. In the first step, the algorithm removes the most time-consuming patient nodes from the routes to ensure the total working time limit of the vehicles. In the second step, the algorithm tries to assign the removed patients to the vehicles whose total working time is less than the max working time by applying the greedy heuristic.

---

**input:** Routes of vehicles $\pi_k$, $k \in K$ in the $x_{curr}$, where, $\pi_k = \{0, \dots v_{i-1}, v_i, v_{i+1}, \dots, 2n+1\}$, travel time between patient $i$ and $j$, $t_{i,j}$, time of arrival at node $i$, $av_{i,k}$, service time of patient $i$, $p_{i,s}$, maximum working time $wTime$ and request bank $R$.
**output:** Feasible solution $x_{curr}$

---

**for** *all vehicle routes*, $\pi_k, k \in K$ *in the* $x_{curr}$,
  **while** $av_{2n+1,k} > wTime$
    **for** all patient nodes $v_i$ in vehicle $k$
      $cost_{v_i,k} = t_{v_{i-1},v_{i+1}} - t_{v_{i-1},v_i} - t_{v_i,v_{i+1}} + p_{v_i,s}$
    **end for**
    **Remove** *patient* $v_{i^*}$ *from vehicle* $k$, $v_{i^*} = \underset{v_i,k}{argmax}\{cost_{v_i,k}\}$ *and*
    **add** *to* $R$
  **end while**
**end for**
**Apply** *greedy insertion to all vehicle routes* $\pi_k$ *with patients that are in request bank* $R$*. Consider the unvisited patients as the remained patients in request bank* $R$*.*
**return** route of vehicles $\pi_k$, $k \in K$

---

**Figure 4.4.** The pseudocode of the repair function to ensure feasibility.

After obtaining a new feasible solution, it is accepted as a current solution for the next iteration if the cost of the new solution is less than that of the current solution. Similar to the concept of the simulated annealing approach, the worse solution than the current solution may also be accepted with some probability to increase the exploration capability of the algorithm. This probability is calculated as $e^{-(f(x_{new})-f(x_{curr}))/T}$, where $f(x_{new})$ and $f(x_{curr})$ are the costs of the new and the current solutions, respectively. $T$ is the temperature having the cooling rate $c$ between $0 < c < 1$.

We also adopted an approach for updating the current solution to stay away from trapping into a local optimal solution and to increase the exploration capability of the algorithm. In our approach, if there is no improvement in the best solution in the last ω iterations, we apply random removal and Regret-3 insertion heuristics to the best-found solution so far and consider the resulting new solution as a current solution for the rest of the iteration.

Lastly, the ALNS-VS algorithm is terminated when both the maximum number of iterations $\theta$ is reached and there is no improvement in the last $\underline{\theta}$ iterations. If the best solution is improved in the last $\underline{\theta}$ iterations, other $\underline{\theta}$ iterations are added to the search process until the condition is met.

# CHAPTER 5
# COMPUTATIONAL EXPERIMENTS AND RESULTS

This chapter comprises computational experiments that were conducted to assess the performance of the proposed ALNS-VS algorithm, answer the research questions defined in Chapter 3, and derive in-depth insights. The UBA and ALNS-VS algorithms described in the previous chapters were implemented in C#. IBM ILOG CPLEX 12.6 optimization solver was used to solve the HHSRP-VS MILP model. CPLEX was run both with standard settings, the aim of which is to find a proven optimal solution, and with various settings that considered various MIP strategies. All of the experiments were conducted on a computer with a 2.50 GHz Intel Core i7-6500U CPU and 16 GB of RAM. Furthermore, the CPLEX solver was limited to 6 hours to obtain solutions.

## 5.1. Problem Instances

A new set of problem instances are generated to evaluate the performance of the proposed algorithms and analyze the characteristics of the HHSRP-VS and the proposed policies. The features of the generated problem instances are described in Table 5.1. We considered 10 to 100 patients with 4 to 12 caregivers in a defined service area. The qualifications for the caregivers were obtained from Liu et al. (2017)'s data set. The patients were randomly located in a circular continuous area that is described by four different radiuses. The reason for considering areas of different sizes is to investigate the effect of area, or in other words, travel distance, on the effectiveness of proposed policies. In each instance class, the single HHC center is located at the center of the area. The distance between nodes in the network determined using the Euclidian distance, ensuring the satisfaction of the triangular inequality. However, it is worth noting that other distance metrics can also be used within the algorithm.

We defined three different types of care requirements concerning their difficulty level as basic, moderate, and difficult care. The reason for considering services with different difficulties is to investigate the effect of service time on the effectiveness of the proposed policies. The service time for each type of care was assumed to be normally distributed by three different means and standard deviations for care. Hence, we considered three different levels of patients' service demand distributions in the instance classes in which the first, second, and third numbers indicate the percentages of the patients that require basic, moderate, and difficult care, respectively. For example, the instance class h100_40_0 indicates that there is a total of 100 patients with 12 caregivers, the patients are randomly distributed in a circular area with a radius of 40 minutes, the demand distribution level is 0 indicating 80%, 15% and the remaining 5% of the patients require basic, moderate and difficult cares (80/15/5), respectively. Last, we generated five instances in each instance class by changing only the locations (coordinates) of the patients. Thus, an instance is described by the last index. For example, the last indices in h100_40_0_1 and h100_40_0_2 indicate that these are the first and the second instances in the instance class h100_40_0 such that only the locations (coordinates) of the patients are differentiated. Thus, there are 48 instance classes and 240 instances in total. Finally, each instance was run in five replications differentiated by five seeds used in a random number generator which resulted in 1200 runs.

**Table 5.1.** Characteristics of the generated problem instances.

| **Feature** | **Description** |
|---|---|
| Number of patients and available caregivers (4 levels) | 10 patients with 4 caregivers; 30 patients with 4 caregivers; 50 patients with 6 caregivers; 100 patients with 12 caregivers |
| Service area radius (4 levels) | 10, 20, 30, and 40 minutes |
| Patients' Demand distributions (3 levels) | Level 0: 80/15/5: 80% basic, 15% moderate, 5% difficult.<br>Level 1: 60/30/10: 60% basic, 30% moderate, 10% difficult.<br>Level 2: 50/30/20: 50% basic, 30% moderate, 20% difficult. |
| Patients service requirement (illness) and corresponding service times (3 levels) | Basic: mean of 10 and standard deviation of 2.5 minutes<br>Moderate: mean of 20 and standard deviation of 5 minutes<br>Difficult: mean of 30 and standard deviation of 7.5 minutes |
| Capacity of vehicles | 2 caregivers |

After generating the instances, a preliminary computational experiment is conducted to validate the model and assess its performance on the small instances (see Figure

5.1). Even a slight increase in the number of patients results in a significant increase in CPU time. Similarly, a slight increase in the number of vehicles and caregivers has a substantial impact on the performance of the MILP. Following parameter tuning experiments, as explained in Chapter 5.2, these instances are solved by the ALNS-VS for comparative analysis The algorithm provides an optimal solution for each instance, with the average gap across five replications being less than 0.1%.

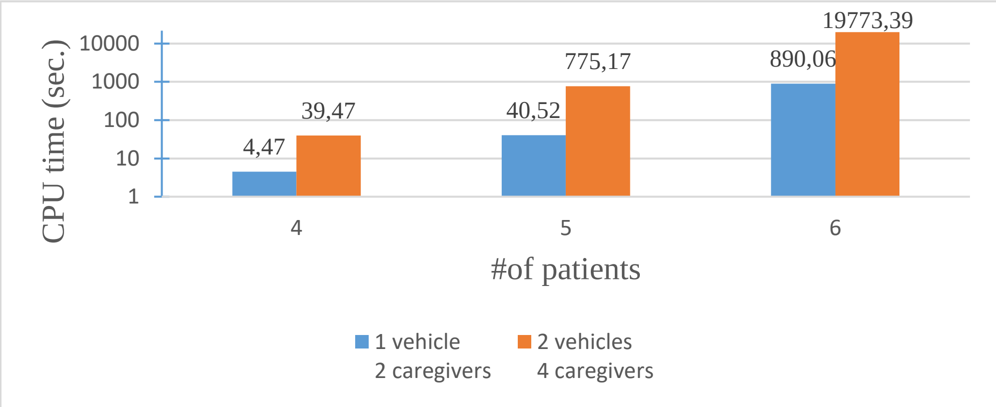



**Figure 5.1.** The performance of MILP on small instances

## 5.2. Parameter Tuning

We considered Ropke and Pisinger (2006a, 2006b)'s settings for many of the fundamental parameters used in a typical ALNS algorithm such as $\theta$, $\alpha$, $\beta$, $\mu$, $\upsilon$ and $c$ as 25000, 0.3, 0.1, 0.1, 0.1, and 0.99975, respectively. We took the additional number of iterations $(\underline{\theta})$ 250 as 10% of $\theta$ (Öztürkoğlu and Mağara, 2019). Furthermore, $\sigma$ and $\phi$ were assumed to be 0.5 and 0.8, respectively as explained in Chapter 4.1. Last, we conducted a full factorial experimental design for the remaining parameters specific to our ALNS-VS algorithm which are update solution iteration $(\omega)$, caregiver swap iteration $(\varphi)$, maximum remove parameter $(\xi)$ and evaporation rate $(\rho)$.

After the preliminary experiments, 6 levels were defined for $\omega$ with ranging from 250 to 1500 with a step size of 250. $\varphi$ has 7 levels with ranging from 50 to 200 with a step size 25. Thus, we aimed to prevent the algorithm from being trapped in a local optimal solution due to the lack of proper caregiver assignment. $\xi$ has 5 levels such as $\xi \in \{0.4, 0.5, 0.6, 0.7, 0.8\}$ and finally $\rho$ has 5 levels as $\rho \in \{0.75, 0.8, 0.85, 0.9, 0.95\}$. In the literature, different values were used for evaporation rate which range from 0.75 to 0.95 (Fuellerer et al., 2009; Yu et al., 2009). In total, we had (6x7x5x5) 1.050 settings for parameters and performed 21.000 runs with 4 different tuning instances and 5 replications obtained by five seeds in a random number generator. To compare the solutions in the experiment, we normalized the best-found solutions for each run: $RPD_{i,j} = \left(\frac{f_{i,j}-f_{min,j}}{f_{min,j}}\right) * 100$, where $RPD_{i,j}$ is the normalized best-found solution of run $i$ for instance $j$; $f_{i,j}$ is the best-found solution by the algorithm in setting-replication pair $i$ for instance $j$, and $f_{min,j}$ is the best solution for instance $j$. These instances comprise of 30 patients, 4 caregivers, 2 vehicles with a capacity of 2 caregivers, area with a radius of 30 minutes. The experiment was conducted on Minitab 19 Statistical Software. The ANOVA and the Response Optimization tests were conducted to investigate the effects of parameters on the quality of the solutions with 95% confidence level. The tests' results showed that the optimal setting is ($\omega$, $\varphi$, $\xi$, $\rho$) = (250,100, 0.5, 0.95). See Table B.1 and Figure B.1 in Appendix B for the details of the test results. Hence, Table 5.2 summarizes the parameter settings used for the proposed ALNS-VS algorithm for the computational experiments.

**Table 5.2.** The parameter settings are used in the proposed ALNS-VS algorithm.

| **Parameters** | **Values** | **Parameters** | **Values** |
|---|---|---|---|
| Total number of iterations ($\theta$) | 25000 | First Shaw parameter ($\alpha$) | 0.3 |
| Additional iteration ($\underline{\theta}$) | 2500 | Second Shaw parameter ($\beta$) | 0.1 |
| Solution update iteration | 250 | Minimum dummy remove | 0.5 |
| Number of caregiver swap | 100 | Maximum dummy remove | 0.8 |
| Minimum remove parameter | 0.1 | Evaporation coefficient ($\rho$) | 0.95 |
| Maximum remove parameter | 0.5 | Noise parameter ($\mu$) | 0.1 |
| Cooling rate ($c$) | 0.99975 | | |

## 5.3. The Effect of the Variations of the Caregiver Swap Heuristic

As previously described in Chapter 3, the first research question aims to investigate the effectiveness of the proposed variations of the caregiver swap heuristic algorithm. As highlighted in Chapter 4.5, this heuristic was designed to look for the best caregiver-vehicle assignment using the pheromone concept from the ACO algorithm with two different visibility heuristics that consider the common and unique number of patients. Thus, we proposed three ALNS-VS algorithms differentiated by the variations of caregiver swap heuristics: (1) ALNS-VS_NoSwap does not include the caregiver swap heuristic, (2) ALNS-VS_Common consists of the heuristic with only common visibility heuristic, and (3) ALNS-VS_Unique considers only unique number of patients as a visibility heuristic.

After solving all 480 problem instances in 5 replications by each algorithm, we tested the following null hypothesis using a paired sample t-tests with a 99% confidence interval in Minitab 19. Whereas the following null hypotheses state that there is no difference between the means of the solutions obtained by the algorithms, the alternative hypotheses state that they are different. $\mu_{noSwap}$, $\mu_{Common}$ and $\mu_{Unique}$ indicate the averages of all of the solutions obtained by ALNS-VS_NoSwap, ALNS-VS_Common and ALNS-VS_Unique, respectively. For the sake of the flow of the manuscript, the solutions of the algorithms were provided in Tables C.1. through C.4 in Appendix C.

- $H_0^a: \mu_{Common} - \mu_{noSwap} = 0$, $H_1^a: \mu_{Common} - \mu_{noSwap} \neq 0$
- $H_0^b: \mu_{Unique} - \mu_{noSwap} = 0$, $H_1^b: \mu_{Unique} - \mu_{noSwap} \neq 0$
- $H_0^c: \mu_{Common} - \mu_{Unique} = 0$, $H_1^c: \mu_{Common} - \mu_{Unique} \neq 0$

Table 5.3 demonstrates the results of the paired t-tests for each hypothesis. As seen in the table, both ALNS-VS_Common and ALNS-VS_Unique are statistically different from ALNS-VS_NoSwap because p-values are less than 0.01. Additionally, ALNS-VS_Common and ALNS-VS_Unique present lower average total flow times than ALNS-VS_NoSwap with an average of 21 and 24 minutes. The analyzes also showed that there is no statistically significant evidence to reject the null hypothesis $H_0^c$ because the p-value (0.163) is greater than 0.01. Hence, we can conclude that ALNS-VS_Common and ALNS-VS_Unique provide statistically similar outputs. However, ALNS-VS_Common caused an average of 3 minutes more working time than ALNS-VS_Unique. Because of this small difference, we decided to use the ALNS-VS_Unique algorithm, hereafter called simply ALNS-VS again, and its solutions for further analyzes and comparisons.

**Table 5.3.** The result of the paired t-tests for the comparisons of the variants of the caregiver swap heuristics.

| | Mean | Std. Deviation | Std. Error Mean | Lower CI | Upper CI | *t* | *df* | *p* |
|---|---|---|---|---|---|---|---|---|
| $\mu_{Common} - \mu_{Unique}$ | 3.00 | 33.21 | 2.14 | -2.56 | 8.57 | 1.40 | 239 | 0.163 |
| $\mu_{Common} - \mu_{noSwap}$ | -21.12 | 43.12 | 2.78 | -28.34 | -13.89 | -7.59 | 239 | 0.000 |
| $\mu_{Unique} - \mu_{noSwap}$ | -24.12 | 44.38 | 2.86 | -31.56 | -16.68 | -8.42 | 239 | 0.000 |

## 5.4. The Effectiveness of the ALNS-VS Algorithm

This chapter aims to provide answers to the second research question in which the effectiveness of the proposed algorithms is investigated in comparison to each other and CPLEX solutions. We limited the running time for processing the HHSRP-VS MILP model to 6 hours (21,600 seconds) because of the complexity of the problem. The quality of the solutions obtained by the CPLEX solver is defined as the discrepancy (GAP) between the best integer objective function value and the relaxed objective function value of the node remaining at the end of the time limit (Öztürkoğlu, 2020). Thus, if we did not obtain the global optimal solution within the time limit, we used the best-found solution so far with its gap for comparisons. We also calculated the computational time of the ALNS-VS and UBA algorithms in terms of seconds for accurate comparisons.

The CPLEX solver did not provide global optimal solutions for the HHSRP-VS problem within the time limit for any of the problem instances. In literature, many HHSRP studies also faced similar problems due to the complexity of the problem (Trautsamwieser and Hirsch, 2011; Trautsamwieser and Hirsch, 2014). We obtain feasible integer solutions only for the instances with 10 patients. For the other instances with more than 10 patients, we couldn't obtain any improved feasible integer solution despite the initial feasible solutions provided by UBA. Table A.1 in Appendix A demonstrates the solutions obtained by CPLEX and UBA for 10-patient instances. In the table, "NA" indicates that no integer feasible solution is available. Whereas the CPLEX provided 16.4% better solutions (see column % Imp.) than the given UBA solutions on average, the average GAP in CPLEX solutions is 40.7%. According to this result, it could be discussed that while the UBA presents a tighter upper bound in a short amount of time (0.05 sec. on average) the optimality GAP seems to be large due to poor lower bound, which is most likely caused by the fractional routing variables of vehicles and caregivers and subtours due to DP policy in linear-programming (LP)-relaxation.

In Table A.2 in Appendix A, we compared CPLEX solutions with ALNS-VS solutions only for 10-patient instances. For 10-patient instances, there are no unvisited patients in both CPLEX and ALNS-VS solutions. However, the ALNS-VS presented a maximum of 19.7% and an average of 6% lower total flow time than the CPLEX solutions only in 1.8 seconds on average.

Since the UBA does not consider the drop off and pick-up policy, its solutions can be considered weak benchmarks for evaluating the effectiveness of the ALNS-VS algorithm (see Table D.1 in Appendix D), especially in instances with more than 10 patients. Therefore, for an accurate comparison, we applied DP local search heuristic introduced in Chapter 4.4 to the solutions developed by UBA. The modified UBA with the DP heuristic is called UBA+DP. Table A.3 in Appendix A presents the aggregated best solutions, which are the averages of the best-found solutions of five instances in an instance class, of ALNS-VS, UBA, UBA+DP, the percentage improvement of UBA+DP over UBA in column "UBA+DP-UBA(%)", and the percentage improvement of ALNS-VS over UBA+DP in column "VS-UBA+DP".

When we applied the DP heuristic to the UBA solutions, we obtained 9.4, 14.6, 13.2 and 12.8 percentage improvement on average in the instances with 10, 30, 50 and 100 patients, respectively. It is obvious that these improvements were achieved by dropping and picking up caregivers on the route. Also, these improvements were achieved with milliseconds more computational effort to solve UBA+DP compared to UBA; where UBA+DP lasted 0.05, 0.2, 0.6, and 1.4 seconds on average in the 10-, 30-, 50-, and 100-patient instances, respectively.

On the other hand, the ALNS-VS solutions presented 13.1, 13.6, 19.3 and 15.9 percent lower total flow time than UBA+DP on average for the 10-, 30-, 50- and 100-patient instances, respectively. When they were compared with UBA solutions, as is expected the percentage improvements increase up to 30%, 35% and 34% for the instances with 30, 50 and 100 patients, respectively. Since ALNS-VS employs the DP policy throughout the iterations in contrast to UBA+DP, some portions of its savings on total flow time over UBA+DP seem to be achieved by additional drop-off and pick-ups. Whereas the caregivers were dropped off 4, 14, 23 and 41 times on average in 10-, 30-, 50- and 100-patient instances in the ALNS-VS solutions, they are 2, 10, 6, 30 in the UBA+DP solutions. It also seems that the number of drop off and pick-up increases as the instance size gets larger. Even though the ALNS-VS algorithm requires proportionally higher computational effort than UBA+DP, 23, 34, 119 seconds in the 30, 50- and 100-patient instances, respectively, we think that this could be negligible from the view of practitioners because a manual solution always takes a very long time and the expected planning time is also usually longer than 5 minutes in practice. Additionally, while there are several unvisited patients in UBA+DP solutions for 12 instances there are no unvisited patients in any of the ALNS-VS solutions. For example, there are averages of 0.4, 1.8, 0.6 and 1.4 unvisited patients in the UBA+DP solutions of h50_40_1, h50_40_2, h100_40_1 and h100_40_2 instance classes, respectively. For the sake of clarity, these unvisited patients were not shown in the tables. As a result, we can conclude that the proposed ALNS-VS algorithm seems to provide reasonably good solutions to the HHSRP-VS problems in a reasonable computational effort.

### 5.5. The Effect of the Drop-off and Pick-up Policy

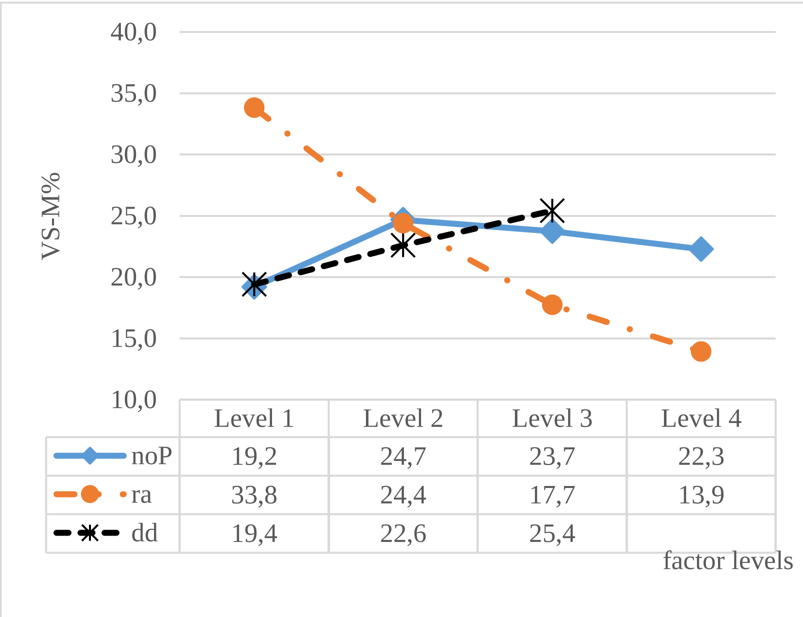
In the previous section, we highlighted that the DP policy seems to reduce the total flow time of caregivers when we compared ALNS-VS, UBA+DP and UBA solutions. Thus, this section aims to investigate the effectiveness of the DP policy in a detailed analysis and answer the third research question. To provide an accurate comparison, we introduced the HHSRP-M problem by removing only the DP policy in HHSRP-VS. Hence, HHSRP-M only allows caregivers to share a vehicle without the possibility of drop-off and pick-up. The MILP model of HHSRP-M could be easily achieved by setting all $y_{i,k,l}$ decision variables to 0 and removing the set of dummy nodes $V_2$ in the HHSRP-VS MILP model.

**Proposition 1.** *The optimal total flow time of caregivers in HHSRP-VS ($f_{VS}^*$) is always less than or equal to that in HHSRP-M ($f_M^*$): $f_{VS}^* \leq f_M^*$.*

**Proof 1.** Suppose that $P_{VS}$ and $P_M$ are the optimal routes in HHSRP-VS and HHSRP-M, respectively. Since DP policy is the only difference between HHSRP-M and HHSRP-VS and it is not allowed in HHSRP-M, $P_M \subseteq P_{VS}$. Hence, it can be written that $f_M^* - \triangle_{DP} = f_{VS}^*$, where $\triangle_{DP}$ indicates savings in total flow time due to drop-off and pick-up. Hence, although the drop-off and pick-up require additional travel time if there exists at least one such a drop-off and pick-up option that reduces flow time of the caregivers by reducing wasted time of the caregivers who wait in the vehicle for the completion time of the occupied caregiver in HHSRP-M; if $\exists \triangle_{DP} > 0$ then $f_{VS}^* < f_M^*$; otherwise $f_{VS}^* = f_M^*$. ■

To compare HHSRP-VS solutions with HHSRP-M in an empirical analysis, we modified the ALNS-VS algorithm by removing its DP local search and dummy node removal heuristics, which were described in Chapter 4. Hence, we called the modified algorithm ALNS-M to solve the HHSRP-M problem. After solving the problem instances with ALNS-M, we observed that there are no unvisited patients in any of the problem instances. We then calculated the percentage difference of total flow time between ALNS-M and ALNS-VS solutions as VS-M%=100*(ALNS-M - ALNS-VS)/ALNS-M to analyze the effect of DP policy on total flow time. Tables E.1 through E4 in Appendix E present the ALNS-M solutions and the percentage differences in details. Table A.3 in Appendix A also presents the aggregated best solutions of ALNS-M and their differences with ALNS-VS. It can be seen in the tables that the implementation of DP policy provides approximately 19, 25, 24 and 22% savings in caregivers' total working time on average for 10-, 30-, 50- and 100-patient instances.

Using the 240 solutions in Tables E.1-E.4 in Appendix E, we also performed a full factorial design of the experiment to investigate the effects of the problem features described in Table 5.1 on the contribution of DP policy at the 95% confidence level. Recall that there are 4 levels of a number of patients ($noP$), 4 levels of service area radiuses ($ra$) and 3 levels of patients' demand distributions ($dd$). The response (dependent variable) is the VS-M%. The results of the full factorial design of experiments (the ANOVA table) are given in Table E.5 in Appendix E. The main factors and their all-level interactions explain 94.27% of the total variation of the response ($R^2$). As seen in Table E.5, $noP$, $ra$ , and $dd$ are significant on the model. Moreover, $ra$ has the largest effect on the contribution of DP policy due to its high "Adj SS" value. This could also be seen in the main effects plot given in Figure 5.1.




| | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|
| noP | 19,2 | 24,7 | 23,7 | 22,3 |
| ra | 33,8 | 24,4 | 17,7 | 13,9 |
| dd | 19,4 | 22,6 | 25,4 | |

**Figure 5.2.** The main effects plot of the factors.

As the service area radius increases from 10 to 40 minutes, the contribution of DP policy steadily decreases from 34% to 14%. This shows that while the impact of DP policy on total flow time is very significant when patients are located in smaller areas such as urban or metropolitan areas, it also provides significant time savings for larger areas. Additionally, the contribution of DP policy steadily increases from 19% to 25% as the level of demand distribution increases. Note that while at the first $dd$ level only 20% of the patients were defined as requiring moderate and difficult care, this rate increases to 50% at the third level. Thus, this suggests that the higher the proportion of patients' difficult service requirements, the greater the contribution of the DP policy. The reason for this increasing contribution of DP policy with increasing demand for difficult services could be that a vehicle prefers to travel between patients rather than waiting in a patient due to high service time. Last, the contribution of the DP policy appeared to be the lowest when the number of patients is the smallest. Its contribution reaches its maximum when there is a moderate number of patients. In our experiments, the policy has shown its highest contribution in the 30-patient problem instances with an average of 25%. The reasons for decreasing contributions when there are few or many patients may be that (1) traveling back and forth due to the DP policy may not be very efficient because a small number of patients is highly likely to be dispersed far from each other, and (2) caregivers' may have longer waiting times at their patients due to the late arrival of the vehicle when there are too many patients to visit.

## 5.6. The Effect of Vehicle Sharing by Multiple Caregivers

As discussed in Chapter 3, one of the common assumptions in existing HHSRP literature is that one vehicle carries only one caregiver. On the contrary, the proposed HHSRP-VS allows multiple caregivers to share a single vehicle for their travels. Hence, it is obvious that sharing a vehicle reduces the necessity of vehicles. However, this could also increase the total flow time of workers due to waiting for each other or a returning vehicle at a patient node. Thus, this section aims to investigate the scenarios where HHSRP-VS may provide potential cost savings and answer the fourth research question. For this purpose and accurate comparison, similar to conventional HHSRP we defined the HHSRP-STD problem in which every single caregiver is assumed to travel with a single vehicle with or without a driver. Therefore, vehicle sharing, and DP policies are irrelevant in the HHSRP-STD. The MILP model of the HHSRP-STD can be easily developed by setting the capacity of all vehicles to 1, $c_k =$

1, setting all $y_{i,k,l}$ decision variables to 0, and removing the set of dummy nodes $V_2$ in HHSRP-VS MILP model.

**Proposition 2. (Best-case scenario)** *If the sets of patients of c caregivers, who can travel in a single shared vehicle, are assigned to the same locations and the patients at the same locations require the same type of service, then the optimal flow time of HHSRP-VS ($f^*_{VS}$), HHSRP-M ($f^*_M$) and HHSRP-STD ($f^*_{STD}$) are equal to each other.* $f^*_{VS} = f^*_M = f^*_{STD}$.

**Proof 2.** Suppose that there are $c$ caregivers who travel with their own vehicle in HHSRP-STD and with a single shared vehicle in HHSRP-M and HHSRP-VS. Suppose that they are assigned to serve the same number of patients ($n$), each located at the same node such as in a mall, apartment or business center: the location of patient $i$ of caregiver $l$ is $v_i^l = v_i$ and $v_i \neq v_j, \forall i \neq j = 1, \dots, n,$ , and $\forall l = 1, \dots, c$. Suppose that the patients located at the same node require the same treatment: the service time of patient $i$ of caregiver $l$ is $p\left(v_i^l\right) = p(v_i), \forall i = 1, \dots, n$ and $\forall l = 1, \dots, c$. Since each caregiver must visit each patient, and patient treatment times are the same at the same location, the optimal tour for all caregivers in HHSRP-STD can be easily computed by solving a TSP for just one caregiver. Hence, suppose that $P = P^l_{STD} = \{v_0^l = 0, v_1^l, \dots, v_n^l, v_{n+1}^l = 0\}, \forall l = 1, \dots, c$ indicates the optimal route of caregivers in HHSRP-STD. If $P$ minimizes the total route length for one caregiver, it must also be the optimal tour of the single shared vehicle in HHSRP-M since all of the caregivers' patients are located at the same points and their service times are the same. Hence,

$$f^l_{STD} = \sum_{i \in P^l_{Std}} \left(t_{v^l_{i-1}, v^l_i} + p\left(v_i^l\right)\right) = \sum_{i \in P} \left(t_{v_{i-1}, v_i} + p(v_i)\right) = T + S, \forall l = 1, \dots, c, \quad (39)$$

where $\sum_{i \in P}\left(t_{v_{i-1}, v_i}\right) = T$ and $\sum_{i \in P} p\left(v_i^l\right) = S$.

$$f^*_{STD} = \sum_{l=1}^{c} f^l_{STD} = c \cdot (T + S) \quad (40)$$

$$f^*_M = \sum_{l=1}^{c} \sum_{i \in P} \left(t_{v_{i-1}, v_i} + p(v_i)\right) = c \cdot (T + S) \quad (41)$$

Because all caregivers in the shared vehicle leave at every patient node $v_i$ and treat their patients simultaneously with the same amount of service time, there is no need to implement a DP policy. Thus, $f^*_{VS} = f^*_M = f^*_{STD}$.■

**Proposition 3. (Practical best-case scenario)** $f^*_{STD}$ *is always less than* $f^*_M$ *when caregivers' patients located at the same nodes require different types of services contrary to Proposition 2.*

**Proof 3. (Based on Proposition 2)** Suppose that caregiver $l$'s patient treatment time at patient node $i$ is not necessarily equal to the treatment times of other caregivers at the same node due to different service requirements: $p(v_i^j) \neq p(v_i^k), \forall i = 1, \ldots, n$ and $\forall j, k = 1, \ldots, c,$ and $j \neq k$ in Proposition 2. The optimal sequence of patients in HHSRP-STD ($P$) can be still obtained by solving a TSP for one caregiver because service times are constant. $P$ also minimizes the total travel time of the single shared vehicle in HHSRP-M. Let $T$ be the total travel time of caregivers or vehicles in the optimal path: $\sum_{i \in P_{Std}^l} \left( t_{v_{i-1}^l, v_i^l} \right) = \sum_{i \in P} \left( t_{v_{i-1}, v_i} \right) = T, \forall l = 1, \ldots, c.$ Let $\sum_{i \in P} p(v_i^l) = S^l$ be the total service times of caregiver $l$'s patients, which are known and constant. The optimal flow time of the caregivers in HHSRP-STD is,

$$f_{STD}^l = \sum_{i \in P_{Std}^l} \left( t_{v_{i-1}^l, v_i^l} + p(v_i^l) \right) = T + S^l, \forall l = 1, \ldots, c \tag{42}$$

$$f_{STD}^* = \sum_{l=1}^c f_{STD}^l = c \cdot T + \sum_{l=1}^c S^l. \tag{43}$$

In HHSRP-M, when $c$ caregivers visit their patients located at the same nodes with a shared vehicle, all other caregivers wait for the caregiver whose patient require the highest treatment time. Hence, $P$ still provides the optimal tour in HHSRP-M, and the optimal flow time in HHSRP-M can be written as in equation (44).

$$\begin{aligned} f_M^* &= \sum_{l=1}^c \sum_{i \in P} t_{v_{i-1}, v_i} + \sum_{l=1}^c \sum_{i \in P} \max(\{p(v_i^1), \ldots, p(v_i^c)\}) \\ &= c \cdot T + c \cdot \sum_{i \in P} \max(\{p(v_i^1), \ldots, p(v_i^c)\}). \end{aligned} \tag{44}$$

As a result, since $S^l < \sum_{i \in P} \max(\{p(v_i^1), \ldots, p(v_i^c)\})$ , $\forall l = 1, \ldots, c$, $f_{STD}^* < f_M^*$. ■

As it is seen in Propositions 2 and 3, sharing a vehicle without DP policy certainly increases caregivers' total flow time except for the best-case scenario. We also know from the previous sections that DP policy provides savings of the flow time when vehicle sharing is allowed. Therefore, to investigate the effect of vehicle sharing with DP and develop in-depth insights, we perform an empirical analysis. For this, we solved HHSRP-STD with the ALNS-STD algorithm, which was developed by removing DP local search, dummy node removal, and caregiver swap heuristics from ALNS-VS, for an accurate comparison.

As defined in Table 3.2, whereas 2 vehicles are assumed to be needed to serve 10 and 30 patients, 3 and 6 vehicles are required for 50 and 100 patients respectively in our problem instances in HHSRP-VS. However, the numbers of vehicles needed are 4, 4, 6, and 12 in HHSRP-STD because every caregiver needs a separate vehicle. Hence, the additional vehicle needs are 2, 2, 3, and 6 (doubled) in HHSRP-STD in those problems. After solving the same problem instances with the new number of vehicles using the ALNS-STD algorithm, we obtained the best-found solutions as given in Tables F.1 through F.4 in Appendix F in details. Table A.3 in Appendix A also presents the aggregated best solutions of ALNS-STD and their percentage improvement over ALNS-VS in column "STD-VS(%)". Because HHSRP-STD is less complex than HHSRP-VS and ALNS-STD requires a few local search heuristics, solving ALNS-STD requires a shorter amount of time: 1.7, 3.2, 5.1, and 19.5 seconds for 10, 30, 50, and 100 patients, respectively, which are much shorter than ALNS-VS that solved the same problems in 1.9, 22.9, 34.1, and 118.6 seconds. Furthermore, as expected the HHSRP-VS causes more total flow time than the HHSRP-STD.

- For 10-patient instances, the caregivers spent about 33% less time, on average 158 minutes, in HHSRP-STD than in HHSRP-VS.
- For 30, 50 and 100 patients, caregivers complete their tour in about 26%, 25% and 25% less time in HHSRP-STD than they are in HHSRP-VS on average, respectively. This leads to totals of 263, 400 and 858 minutes of savings on average for the same problem sets, respectively.

The abovementioned results showed that HHSRP-STD provides a considerable amount of savings in total flow time of caregivers' working time with a cost of additional vehicles, which may be special vehicles equipped with healthcare equipment. Because of this trade-off, we take our analysis further and compare HHSRP-VS and HHSRP-STD in light of the total cost of providing care services to find out deeper insights. For this purpose, we performed a break-even analysis.

Suppose that $TC_{STD}$ and $TC_{VS}$ are the total daily monetary cost of managing home health care services in HHSRP-STD and HHSRP-VS, respectively. Let $C_V$ be the hourly cost of vehicle ownership or usage that may consist of the rental or payment cost per hour of a vehicle, the hourly wage of a driver, the cost of fuel consumption for an hour, and all other costs related to the usage of the vehicle. Similarly, let $C_L$ be the average hourly cost of caregivers that may include their salaries, insurances, bonuses, and lunch payments. Last, $f^*_{STD}$ and $f_{VS}$ indicate the best objective function values (total flow time of caregivers in hours) of the HHSRP-STD and HHSRP-VS problem instances solved by ALNS-STD and ALNS-VS algorithms, respectively. Recall that $c$ is the capacity of the vehicles in HHSRP-VS. Thus, $TC_{STD}$ and $TC_{VS}$ can be simply written $TC^*_{STD} = f^*_{STD} * C_V + f^*_{STD} * C_L$ and $TC^*_{VS} = \frac{f^*_{VS}}{c} * C_V + f^*_{VS} * C_L$ .

The first terms in these equations indicate the total cost of vehicle ownership and the second terms identify the total cost of labor. In $TC^*_{VS}$, $f^*_{VS}$ is divided by $c$ to calculate the flow time of vehicles. Hence, the breakeven rate ($BER$) can be calculated by equation (45). Proposition 4 shows that the denominator is always positive.

$$BER = \frac{C^*_V}{C^*_L} = \frac{(f^*_{VS} - f^*_{STD})}{\left(f^*_{STD} - \frac{f^*_{VS}}{c}\right)}, \tag{45}$$

**Proposition 4.** *In the optimal solutions of HHSRP-STD ($f^*_{STD}$), HHSPR-M ($f^*_M$), and HHSRP-VS ($f^*_{VS}$), $\frac{f^*_{VS}}{c} \leq \frac{f^*_M}{c} < f^*_{STD}$.*

**Proof 4.** Suppose that $P_{STD} = \{P^l_{Std}, \forall l = 1 \ldots c\}$ is the set of optimal assignments and routes of $c$ caregivers/vehicles in the optimal solution of a HHSRP-STD, where $P^l_{STD} = \{v^l_0 = 0, v^l_1, \ldots, v^l_m, v^l_{m+1} = 2n + 1\}$ indicates the optimal route of caregiver $l$. Let $e^l_0 = \{v^l_0, v^l_1\}$ and $e^l_1 = \{v^l_m, v^l_{m+1}\}$ be the first and the last edges that are traversed in the route of caregiver $l$, respectively. Let $T^l$ be the total travel time of caregiver $l$, hence, similar to equation (42),

$$f^l_{STD} = \sum_{i \in P^l_{Std}} \left(t_{v^l_{i-1}, v^l_i} + p(v^l_i)\right) = T^l + S^l \tag{46}$$

$$f^*_{STD} = \sum_{l=1}^{c} f^l_{STD} = \sum_{l=1}^{c} T^l + \sum_{l=1}^{c} S^l \tag{47}$$

Suppose that caregivers have no common skills or there is no patient who can be treated by more than one caregiver. Suppose that each patient has a different service time and the locations of patients treated by each caregiver are placed apart from each other like in different regions or zones. See Figure 5.2 for an example representation of two caregivers' patients and paths. Contrary to Proposition 3, these assumptions define the worst case of the distribution and the assignments of patients. Because $P^l_{STD}$ identifies the optimal path for each caregiver, in the optimal solution of HHSRP-M the vehicle must follow through each caregivers' path with an elimination of return to the HHC center after a caregiver's service completed. The caregivers who completed serving their patients must travel through the other caregivers' paths and wait in the shared vehicle until all caregivers completed their service. Hence, when we combine $P_M = P^1_{STD} \cup P^2_{STD} \ldots \cup P^c_{STD} \cup \{\Delta^a\}/\{\Delta^s\}$ where $\Delta^a$ and $\Delta^s$ indicate the additional and the removed paths to complete a single circuit. Let us consider the example in Figure 5.2. We can develop optimal tour of HHSRP-M by combining two caregivers' routes $P^1_{STD}$ and $P^2_{STD}$ into one route of a vehicle $P_M$. Suppose that the vehicle visits patients in $P^1_{STD}$ then in $P^2_{STD}$ for minimum flow. Hence, $P_M = P^1_{STD}/\{e^1_1\} \cup \{e_{1,2}\} \cup P^2_{STD}/$

$\{e_0^2\}$, where $e_{1,2} = \{v_m^1, v_1^2\}$ is the connection edge. For the example in Figure 5.2, $P_{STD}^1 = \{0, 1, 2, 3, 0\}$, $P_{STD}^2 = \{0, 4, 5, 6, 7, 0\}$ and $P_M = \{0, 1, 2, 3, 4, 5, 6, 7, 0\}$ where $e_1^1 = \{3,0\}$, $e_0^2 = \{0,4\}$ were removed from $P_{STD}^1$ and $P_{STD}^2$, respectively and connection edge $e_{1,2} = \{3,4\}$ was added.

Let $\mathcal{H}$ be the set of caregiver pairs in the shared vehicle in the optimal route of HHSRP-M. So, we can write the optimal flow time as

$$f_M^* = c \cdot \left[\sum_{l\in L}\sum_{i\in P_{Std}^l} t_{v_{i-1}^l, v_i^l} + \sum_{(i,i+1)\in\mathcal{H}, i\in\frac{L}{\{c\}}}\left(t_{e_{i,i+1}} - t_{e_1^i} - t_{e_0^{i+1}}\right)\right] + c \cdot \sum_{l\in L}\sum_{i\in P_{Std}^l} p(v_i^l) \tag{48}$$

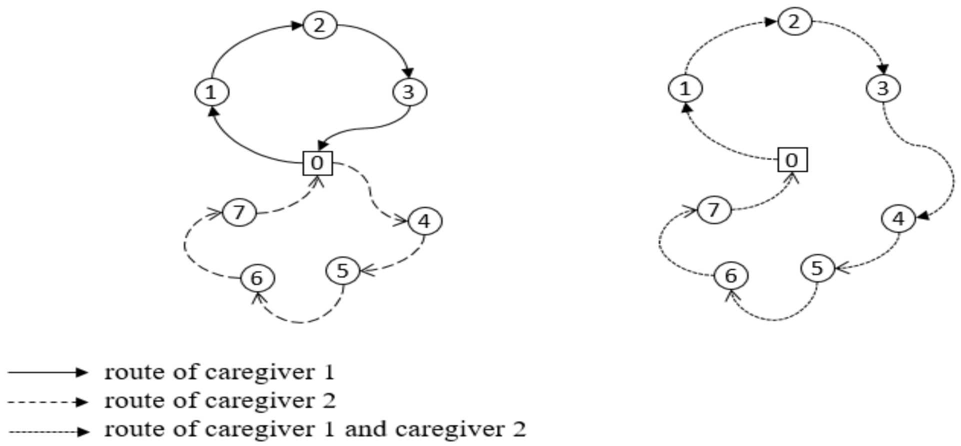



**Figure 5.3.** The representation of the optimal paths of two caregivers in the worst case.

In equation (45), the first and the second terms indicate the portion of total travel and service times in the total flow time of caregivers. With the triangle inequality assumption, the term $\sum_{(i,i+1)\in\mathcal{H}, i\in\frac{L}{\{c\}}}\left(t_{e_{i,i+1}} - t_{e_1^i} - t_{e_0^{i+1}}\right)$ in total travel time is always non-positive. This can be seen in the example given in Figure 5.2 $e_{1,2} < e_1^1 + e_0^2$. Hence, $f_M^*$ can be written as in equation (49).

$$f_M^* = c \cdot \sum_{l=1}^{c} T^l + c \cdot \sum_{l=1}^{c} S^l + c \cdot \Delta, \tag{49}$$

$$\frac{f_M^*}{c} = \sum_{l=1}^{c} T^l + \sum_{l=1}^{c} S^l + \Delta \le f_{STD}^* \tag{50}$$

Finally, with the help of Proof 1, $\frac{f_{VS}^*}{c} \le \frac{f_M}{c} < f_{STD}^*$.■

Tables F.1 – F.4 in Appendix F presents the $BER$ values calculated for each solution in detail. Table A.3 in Appendix A demonstrates the average $BER$ values for each instance class. Hence, if $\exists \frac{c_V}{c_L} > BER$, HHSRP-VS may be preferable to HHSRP-STD due to lower total cost of service; otherwise, HHSRP-STD is superior to HHSRP-VS in terms of the total cost of service. When we conducted a full factorial design of experiment with factors $noP$, $ra$, and $dd$ and a response $BER$, the analysis showed that every main factor and only $noP * ra$ two-way interaction is significant with a model of 76.75% $R^2$. The ANOVA table for this analysis is given in Table 5.4. Additionally, the number of patients ($noP$) and service area radius ($ra$) have the largest effect on $BER$ due to their high Adj SS values.

**Table 5.4.** The ANOVA table for break-even ratios.

| ***Source*** | ***DF*** | ***Adj SS*** | ***Adj MS*** | ***F-Value*** | ***p-Value*** |
|---|---|---|---|---|---|
| $\boldsymbol{noP}$ | 3 | 33.95 | 11.32 | 63.05 | 0.000 |
| $\boldsymbol{ra}$ | 3 | 57.57 | 19.19 | 106.93 | 0.000 |
| $\boldsymbol{dd}$ | 2 | 7.49 | 3.75 | 20.88 | 0.000 |
| $\boldsymbol{noP * ra}$ | 9 | 8.41 | 0.93 | 5.21 | 0.000 |
| $\boldsymbol{noP * dd}$ | 6 | 3.09 | 0.52 | 2.87 | 0.011 |
| $\boldsymbol{ra * dd}$ | 6 | 1.10 | 0.18 | 1.02 | 0.413 |
| $\boldsymbol{no * ra * dd}$ | 18 | 2.11 | 0.12 | 0.65 | 0.854 |
| ***Error*** | 192 | 34.46 | 0.18 | | |
| ***Total*** | 239 | 148.19 | | | |

Further analysis was also conducted to gain more insights into the effects of the main factors on $BER$. First, the Bonferroni t-test was used to examine the statistical significance of the different levels of $noP$, $ra$ and $dd$ with a 95% confidence level. If there is no statistically significant difference between the levels, then they are grouped and shown symbolically as demonstrated in Table 5.5.

**Table 5.5.** Multiple comparison test results for $BER$ according to the problem features.

| $noP$ | Mean | | $ra$ | Mean | | $dd$ | Mean | |
|---|---|---|---|---|---|---|---|---|
| 10 | 1.99 | A | 40 | 1.91 | A | 0 | 1.57 | A |
| 30 | 1.30 | B | 30 | 1.69 | A | 1 | 1.37 | B |
| 100 | 1.08 | B C | 20 | 1.19 | B | 2 | 1.13 | C |
| 50 | 1.06 | C | 10 | 0.64 | C | | | |

As can be seen in Table 5.5 whereas the problems with 10 patients are statistically different from the others, it is interesting that there is no statistical difference between the problem instances of 30 and 100 patients and between 50 and 100 patients. The $BER$ values for the 10-patient problem instances are approximately twice as high as those for the other 50- and 100-patient problem instances. This result may be consistent with the observation made in Chapter 5.5, where the contribution of DP policy to flow time savings was lowest when the number of patients is smallest. The analysis also revealed that while there was no statistical difference between service areas with a radius of 30 and 40 minutes, there was a difference among these and other service areas.

Furthermore, the $BER$ decreases as the service area gets smaller. This result is also consistent with the observation made in Chapter 5.5 that the reduction in flow time is greatest when the service area is smallest. For example, in a 10-minute service area, HHSRP-VS has a lower total cost than HHSRP-STD as long as the hourly vehicle cost to hourly labor cost ratio is greater than 0.64. In other words, if the hourly labor cost is 100 units and the hourly vehicle cost is more than 64 units, car sharing with a drop-off policy may be preferred compared to the case where everyone uses their own vehicle to reduce the total cost in a 10-minute service area. Since labor costs may be higher than vehicle usage costs in developed countries, especially in the health sector, BER values less than 1 may indicate that the chance of using a shared vehicle with the DP policy is higher.

However, the opposite might also be true for developing countries, where ownership or using cost of proper vehicles for home health care services might be more expensive than cost of labor. According to the results, we can say that vehicle sharing with DP policy provides cost savings mostly when the hourly vehicle cost is higher than the labor cost since $BER$ is mostly higher than 1 in many of the cases as can be seen in Table 5.5. Additionally, as shown in Proposition 2, $BER$ is equal to 0 in the best-case scenario where $f_{VS}^{*} = f_{STD}^{*}$. Hence, HHSRP-VS always costs less than HHSRP-STD, no matter how high the hourly labor cost in the best-case scenario. Last, the average $BER$ is statistically different at each level of the patient's demand distribution. The average $BER$ decreases as the percentage of difficult care requirement increases.

Figure 5.4 also demonstrates that the average $BER$ generally decreases as the number of patients increases, the service area decreases, and the level of service patients' demand distribution increases. If the practical $\frac{c_V}{c_L}$ can be assumed to be 1, where the hourly costs of vehicle ownership labor cost are equal, then we can say that sharing vehicles with DP policy provides savings in total service cost,

- when the service area is 10 minutes away from the HHC center regardless of the number of patients and the difficulty of the service requirement.
- when the service area is 20 minutes away from the HHC center and the number of patients in the area is more than 30.
- when the patients' demand distribution is 50/30/20, where the difficult and moderate care requirements are high, and there are more than 30 patients.

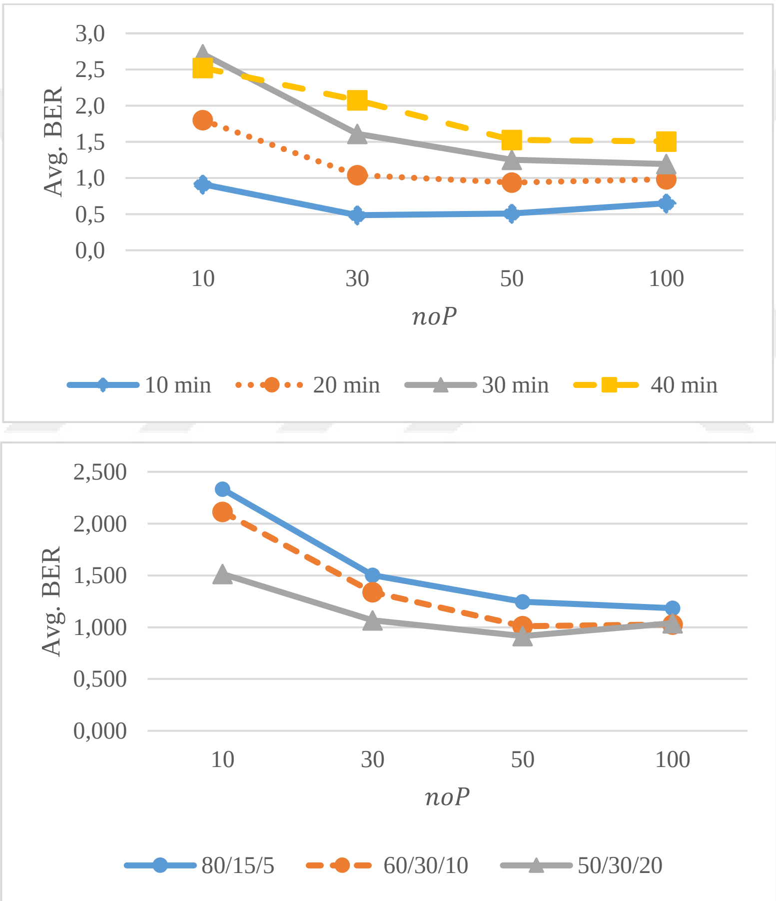



**Figure 5.4.** The changes on average $BER$ over service area (top) and the patients' demand distributions (bottom).

Finally, we explore the effect of patient density in an area in terms of "number of patients located per unit service area ($PperA$) in terms of kilometer$^2$ where a vehicle travels 60 km/h on average. $PperA = noP/(\pi * ra^2)$, where $\pi$ was taken 3.14. As seen in Figure 5.5, the average $BER$ mostly decreases as $PperA$ decreases. For example, the average BER is 0.98 when there are 0.08 patients in a unit service area, while it decreases to 0.48 when there are 0.096 patients in the same area. We can conclude that it is highly likely that sharing vehicles with DP policy will result in less total cost than HHSRP-STD when $PperA$ is greater than 0.075. Hence, this result also supports our previous observations, such that the denser the patients in an area the superior the HHSRP-VS model.

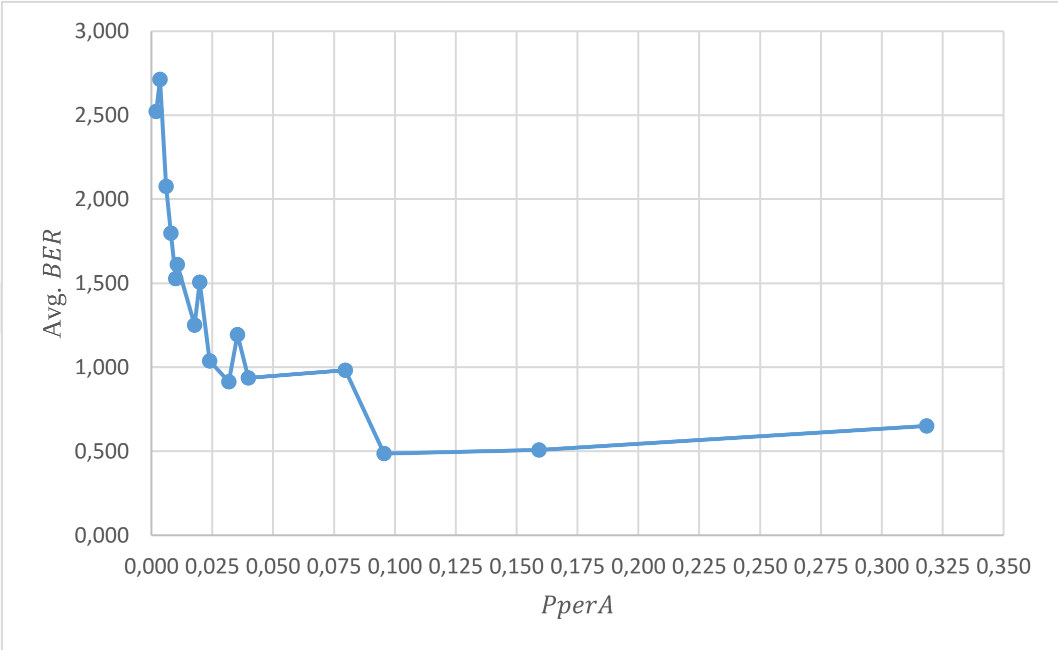



**Figure 5.5.** The effect of $PperA$ on average $BER$ values

# CHAPTER 6
# HOME HEALTHCARE DECISION SUPPORT SYSTEM AND ITS IMPACT IN HHC SYSTEM

A Decision Support System (DSS) is an information system that permits users to seek help from computer technology during decision making process. It is a combination of data, information, software, analysis, and mathematical model which helps people to understand the complex systems and solution methodology of these systems. With an aim of assisting experts (end-users) in their decision-making, a prototype of home healthcare decision support system (HHDSS) has also been developed for the HHRSP under study. To implement a desktop application of the proposed system, different libraries such as matplotlib[1], NumPy[2], scikit-learn[3], and Tkinter have been used, in which the Tkinter is the standard GUI library for python. Tkinter provides a powerful object-oriented environment to the GUI toolkit. The integration of python and Tkinter allows users to create a GUI application through a fast and easy process.

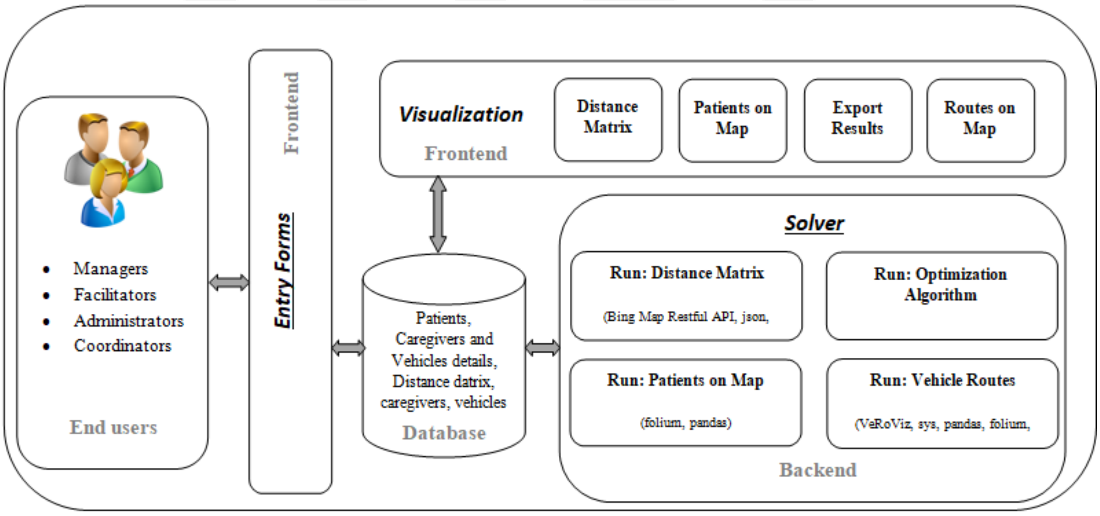



**Figure 6.1.** Architecture of HHDSS

## 6.1. Architecture of HHDSS

The designed HHDSS is a model-driven single installation system that has all the

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[1] Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python and is accessible from https://matplotlib.org.
[2] Numpy is an open scientific computing Python library and is accessible from https://numpy.org.
[3] Sklearn or scikit-learn is an open machine learning Python library which and is accessible from https://scikit-learn.org/stable/

essentials programs and databases stored locally. The HHDSS architect is divided into three main parts. "Data Entry", "Solver" and "Visualization" as shown in Figure 6.1. Through the "Entry Forms", necessary information of patients, caregivers, and vehicles data is entered in the database of the system which is saved in .xlsx format.

"Solver" is further divided into four different modules which are distance matrix generator, patients' location on the map, optimization algorithm, and routes of the vehicle on a map. These modules can be operated by the respective buttons which exploit the required data available in the database to generate the desired results. These buttons include "Run: Distance Matrix", "Run: Patients on Map", "Run: Optimization Algorithm" and "Run: Vehicles Routes". In short, all the buttons starting with "Run:" are part of "Solver" and will use to run the code for the desired operation.

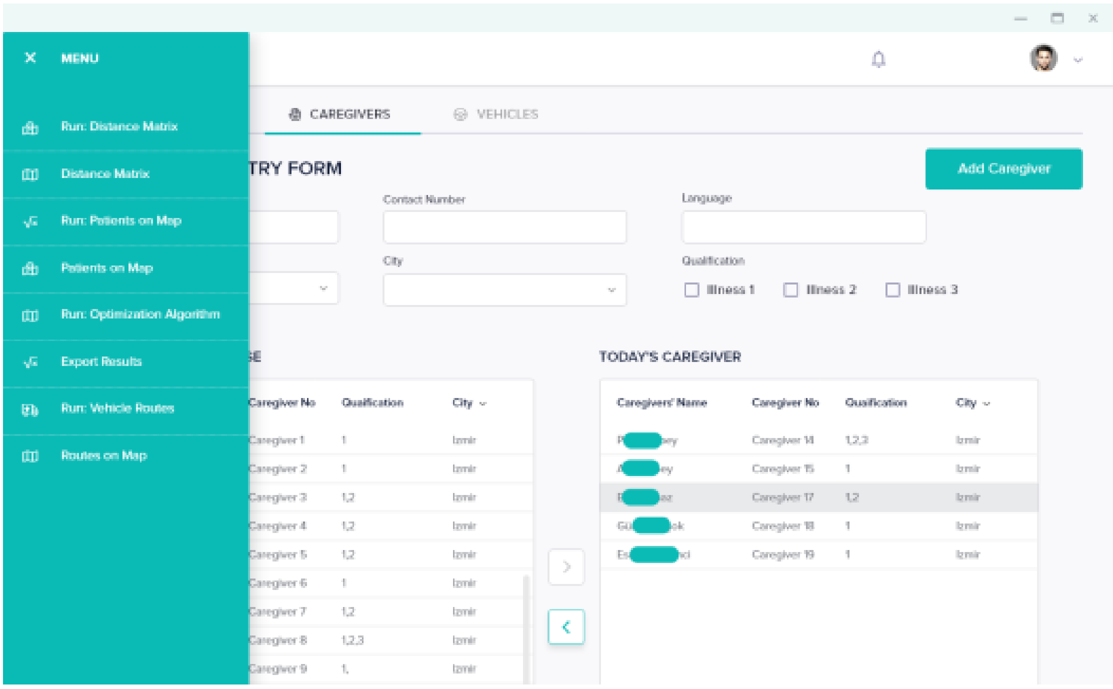



**Figure 6.2.** Outlook of the HHDSS

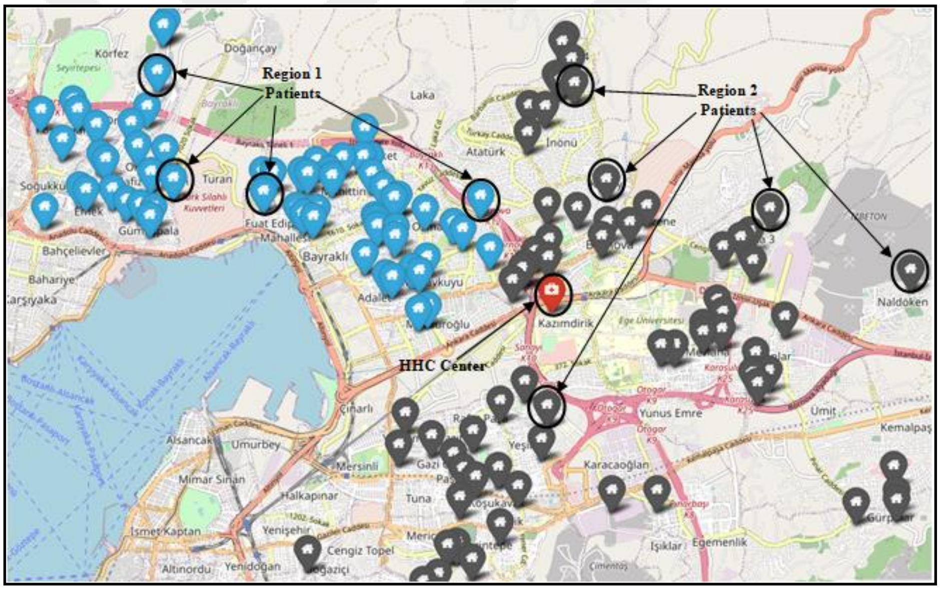
The data which is in the database or entered through the "Patients Entry Form" are used to calculate the road distances from every node to every node in the current network by clicking the "Run: Distance Matrix" button. The actual road distance matrix is obtained by using Bing Maps Distance Matrix API. A Python code is developed using JSON and urllib[4] libraries. The Bing API provides travel times and

[4] urllib is a python package for dealing with URLs. It can freely accesed from

distances for a set of origins and destinations. The generated distance matrix can be seen in .xlsx and .txt format by clicking the "Distance Matrix" button from the menu.

To get a better idea of patients' locations, a code is written by using the folium[5] library and can be run by clicking the "Run: Patients on Map" button. For the input, the data that was used for calculating the distance matrix is utilized here also through the panda's library. The results of that code can be seen as an HTML file by clicking the next button of the pair i.e., “Patients Map".

The proposed ALNS-VS algorithm is used to find the caregiver-patient assignment and the routes of vehicles. The ALNS-VS takes three inputs that are distance matrix, and information of patients, and the caregivers. By clicking the "Run: Optimization Algorithm", an .exe file is executed from the Python environment to generate the result. The result of schedule and route optimization can be seen through the "Export Results" button.




*Region 1: Bayrakli (Izmir); Region 2: Bornova (Izmir)

**Figure 6.3.** Example representation of patients' locations on the map in Izmir, Turkey

A code for showing the route of vehicles on the actual road network is written in Python and is shown by clicking "Run: Vehicle Routes" button on the interface. An open-source package, VeRoViz (Vehicle Routing Visualization), is used to generate

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https://docs.python.org/2/library/urllib.html

[5] Folium developed by Story, R (2013) is a python library and be freely accessed from https://pypi.org/project/folium/

and visualize the nodes and vehicle routes on the road networks. Figure 6.3 shows an example visualization of the locations of patients on a map that needs to be visited with a distinct color variation depending on the area in Izmir, Turkey. This map is obtained by running the backend code of the "Run Code: Map on Patients" button.

## 6.2. An Example on the Data Set of Covid-19

This section aims to present the potential use of the developed DSS powered by the developed ALNS-VS algorithm with real road distances. For this, the approximate locations of COVID-19 patients present in two neighboring districts of the three biggest cities of Turkey, namely Ankara, Istanbul, and Izmir have been extracted. These three cities are at high risk of spreading the virus that causes COVID-19 to people (COVID-19 Istanbul, Ankara and Izmir density and risk map, September 07, 2020) and on average 200-250 positive cases are being observed per day just in Izmir. Neighboring districts were selected from these cities in terms of importance in diplomatic affairs, tourism, and their role as financial centers. These extractions of the approximate locations from these districts were made through the heatmap available in the mobile application "Life Fits into Home". This mobile application was developed and continuously updated by the digital transformation office of the Turkish government. The main objective behind this application is to protect its citizens from being exposed to dangerous areas during the current pandemic. Figure 6.4 provides example heat maps of COVID-19 patients from various provinces in Turkey that were extracted from the application.

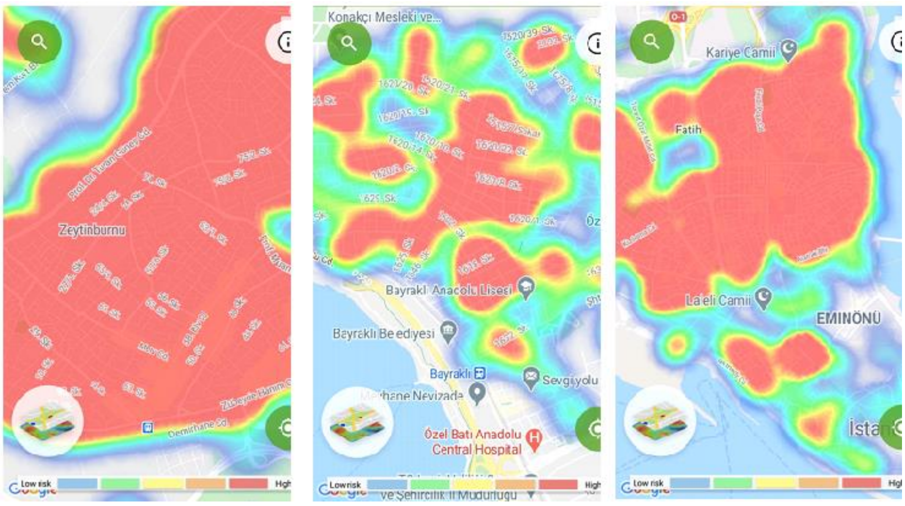



**Figure 6.4.** Heat map images from “Life Fits into Home” application

### 6.2.1. Test Instances

Small to large-sized instances are generated in the selected districts within the cities of Istanbul, Ankara, and Izmir in Turkey. The largest government hospital, located within the neighborhoods of these selected districts, has been designated as the HHC (Home Health Care) center to provide an enough number of caregivers to serve all the patients. Details about the selected districts in the three largest cities of Turkey, along with the number of patients in each city and their respective selected districts, are presented in Table 6.1. The symbols representing the cities, which will be used to represent instances, are enclosed in brackets alongside their names. The table also provides information on the minimum, average, and maximum distances of patients from the HHC center, displayed on the right-hand side.

**Table 6.1.** The details of the selected neighborhood with respect to their cities

| City | Neighboring Districts | # Patients | Land Areas ($km^2$) | Total # Patients | Distance to HHC (km) | | |
|---|---|---|---|---|---|---|---|
| | | | | | Min. | Avg. | Max. |
| Ankara (AN) | Çankaya (C) | 195 | 268 | 344 | 0.68 | 12.6 | 24 |
| | Altındağ (A) | 149 | 174.5 | | | | |
| Istanbul (IS) | Fatih (F) | 101 | 13.08 | 184 | 0.78 | 4.78 | 11.61 |
| | Zeytinburnu (Z) | 83 | 12.08 | | | | |
| Izmir (IZ) | Bornova (O) | 68 | 224 | 131 | 1.44 | 6.56 | 12.71 |
| | Bayraklı (B) | 63 | 30 | | | | |

In total there are six classes of instances generated for each city that are given in Table 6.2. These instances are going to be represented in the format like 50SO1, 100IS2, ANAC344 which means 50 randomly selected patients from Bornova in the first instance, 100 randomly selected patients from whole Istanbul out of 184 patients in total in the second instance, and all patients of Ankara (A+C) that are 344 respectively. Three different types of services for the caregivers have been considered based on our experience and interviews with practitioners. Type-I service is assumed to be for diagnosing the COVID-19 test such as the PCR test. In this type of service, a caregiver visits the patient to take samples for diagnosing the disease. Type-II service is assumed to be for the simple medication and varying of positive COVID-19 patients who do not have a chronic disease, whereas the Type-III service includes the medication of positive COVID-19 patients and their chronic diseases but not in a high-risk group. Patients who are in the high-risk group are not included because they have to be treated in hospitals or in some specially built isolation centers.

**Table 6.2.** The details of the different classes of instances within cities

| Classes of Instances (Ankara) | Classes of Instances (Istanbul) | Classes of Instances (Izmir) |
|---|---|---|
| SA: Sample of Altindag<br>SC: Sample of Cankaya<br>AN: Sample of Ankara<br>ANA: All Altindag<br>ANC: All Cankaya<br>ANAC: All Ankara (A+C) | SF: Sample of Fatih<br>SZ: Sample of Zeytinburnu<br>IS: Sample of Istanbul<br>ISF: All Fatih<br>ISZ: All Zeytinburnu<br>ISFZ: All Istanbul (F+Z) | SO: Sample of Bornova<br>SB: Sample of Bayrakli<br>IZ: Sample of Izmir (B+O)<br>IZB: All Bayrakli<br>IZO: All Bornova<br>IZBO: All Izmir (B+O) |

Therefore, the proposed service types are a standard procedure with low variability. However, the service times of different types of services differ from one another. The mean and coefficient of variation values are estimated for each type of service. The mean service time values of Type-I, Type-II, and Type-III services are assumed to be 10, 15, and 20 minutes, respectively. The coefficient of variation of all types of services is estimated as 0.25 due to low variability caused by cultural behaviors. In addition, after talking to practitioners, we assumed that 60%, 30%, and 10% of patients seek Type-I, Type-II, and Type-III treatments, respectively. On the other hand, hierarchical qualification levels are determined for caregivers which means all of the caregivers can treat Type-I services, 50% of caregivers can treat Type-II, and only 20% of caregivers can treat Type-III services. Lastly, caregivers work between 9:00 and 18:00 and must have 60 minutes lunch break between 11:00 and 14:00. The details of the generated patients' and caregivers' data concerning types of services are given in Table 6.3 in which the number of caregivers has been defined with the assumption to represent practical concerns.

### 6.2.2. Results

Table 6.4 demonstrates the summary of the results that are the averages of the corresponding test instances of COVID-19 patients' data concerning the city and patients' size. These results are obtained using the developed DSS. The average of the total travel time spent by caregivers for all corresponding instances is identified by

“Avg. TTT” in minutes whereas “Avg. TWT” shows how much time all caregivers spent for servicing and traveling in a single day on average. For an instance, two caregivers spent 44.46 minutes in traveling and 437.46 minutes (implicitly 393 min. for caring) for both servicing and traveling all 30 patients in Bayrakli on average. Hence, the average total service time can be calculated by (Avg. Total Working Time - Avg. Total Travel Time.” “Avg. Cpu” is the average computational time to obtain a solution, and “Std. Dev.” is the standard deviation of caregivers’ travel time.

**Table 6.3.** The details of patients and caregivers

| # of patients | # of caregivers | # of demands | | | # available caregivers with respect to the type of illnesses. | | |
|---|---|---|---|---|---|---|---|
| | | Type-I | Type-II | Type-III | Type-I | Type-II | Type-III |
| 30 | 2 | 18 | 9 | 3 | 2 | 1 | 1 |
| 50 | 3 | 30 | 15 | 5 | 3 | 2 | 1 |
| 100 | 5 | 60 | 30 | 10 | 5 | 3 | 1 |
| 63 (Bayrakli) | 4 | 38 | 19 | 6 | 4 | 2 | 1 |
| 68 (Bornova) | 4 | 41 | 20 | 7 | 4 | 2 | 1 |
| 131 (Izmir) | 7 | 79 | 39 | 13 | 7 | 4 | 1 |
| 40 | 2 | 24 | 12 | 4 | 2 | 1 | 1 |
| 60 | 3 | 36 | 18 | 6 | 3 | 2 | 1 |
| 100 | 5 | 60 | 30 | 10 | 5 | 3 | 1 |
| 101 (Fatih) | 6 | 61 | 30 | 10 | 6 | 3 | 1 |
| 83 (Zeytinburnu) | 5 | 50 | 25 | 8 | 5 | 3 | 1 |
| 184 (Istanbul) | 10 | 110 | 55 | 19 | 10 | 5 | 2 |
| 75 | 4 | 45 | 23 | 7 | 4 | 2 | 1 |
| 100 | 5 | 54 | 27 | 9 | 5 | 3 | 1 |
| 149 (Altindag) | 8 | 89 | 45 | 15 | 8 | 4 | 2 |
| 195 (Cankaya) | 10 | 117 | 59 | 19 | 10 | 5 | 2 |
| 344 (Ankara) | 18 | 206 | 104 | 34 | 18 | 9 | 4 |

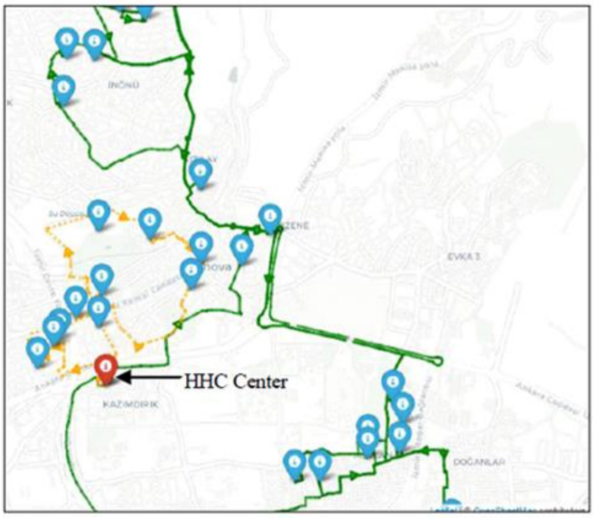
Considering the instances of Izmir in which it can be seen that the travel time increases when patients from both the neighboring districts are combinedly selected rather than dealing with them individually. This phenomenon is not seen among the instances of Istanbul and Ankara. The reason for this is that in Istanbul the land areas of both the districts are very small as compared to the land areas of other cities and the patients are located very close to each other due to high urbanization. In the case of Ankara, the land area of Çankaya individually is greater than the sum of the areas of Bornova and Bayrakli, and the patients are spread all over the districts of Ankara. This can also be observed by comparing the average travel time spent by the caregivers of 131IZBO, 184ISFZ and 344ANAC that are 157.31, 152.10, and 599.96 minutes, respectively.

**Table 6.4.** The results of COVID-19 instances

| **IZMIR** | | | | | **ISTANBUL** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Instance Clusters** | **Avg. TTT** | **Std. Dev.** | **Avg. TWT** | **Avg. CPU** | **Instance Clusters** | **Avg. TTT** | **Std. Dev.** | **Avg. TWT** | **Avg. CPU** |
| 30SB | 44.46 | 1.84 | 437.46 | 96.12 | 40SF | 37.30 | 2.04 | 564.49 | 172.16 |
| 30SO | 53.18 | 3.19 | 449.93 | 70.76 | 40SZ | 50.54 | 3.40 | 557.22 | 147.44 |
| 30IZ | 67.04 | 5.39 | 459.45 | 77.00 | 40IS | 50.59 | 2.32 | 606.25 | 162.64 |
| 50SB | 60.16 | 1.88 | 712.92 | 179.32 | 60SF | 49.86 | 2.45 | 836.84 | 287.88 |
| 50SO | 72.22 | 1.83 | 720.15 | 162.32 | 60SZ | 66.96 | 1.55 | 831.39 | 270.64 |
| 50IZ | 88.11 | 5.49 | 739.42 | 157.20 | 60IS | 66.00 | 1.49 | 863.92 | 287.84 |
| 100IZ | 142.40 | 4.51 | 1278.76 | 695.56 | 100IS | 98.67 | 3.85 | 1420.66 | 760.56 |
| 68IZB | 87.96 | 1.56 | 1408.96 | 299.80 | 101ISF | 72.70 | 0.71 | 1403.25 | 813.4 |
| 63IZO | 74.51 | 3.40 | 1396.51 | 317.40 | 83ISZ | 91.95 | 1.37 | 1193.86 | 559.8 |
| 131IZBO | 157.31 | 4.07 | 1877.43 | 825.80 | 184ISFZ | 152.10 | 5.74 | 2590.32 | 1238.4 |
| **ANKARA** | | | | | | | | | |
| **Instance Clusters** | **Avg. TTT** | **Std. Dev.** | **Avg. TWT** | **Avg. CPU** | **Instance Clusters** | **Avg. TTT** | **Std. Dev.** | **Avg. TWT** | **Avg. CPU** |
| 75SA | 121.07 | 2.09 | 1096.61 | 423.12 | 100AN | 262.91 | 12.26 | 1604.52 | 652.32 |
| 75SC | 207.08 | 14.16 | 1177.70 | 385.20 | 149ANA | 203.23 | 2.38 | 2167.06 | 993 |
| 75AN | 206.17 | 8.57 | 1187.38 | 380.04 | 195ANC | 326.99 | 10.03 | 2886.16 | 1158 |
| 100SA | 273.94 | 9.51 | 1613.66 | 631.56 | 344ANAC | 599.56 | 17.11 | 5104.66 | 1678.8 |
| 100SC | 159.07 | 3.69 | 1489.73 | 732.28 | | | | | |

It can also be observed that the caregivers spent the bigger portion of their total working time in giving service to their patients and not more than 18% of the total working time was spent on traveling in any of the instances. The duration of the service time of caregivers is completely dependent on the number of patients present in the respective instance. As the number of patients increases, the total service time also increases. Figure 6.5 demonstrates the caregiver routes of one of the 40SZ and 30SO instances, respectively. The sequence of visiting the patients is exactly delineated by the HHDSS.


(a) Zeytinburnu neighborhood (Istanbul) with 2 caregivers covering 40 patients




(b) Bornova neighborhood (Izmir) with 2 caregivers covering 30 patients

**Figure 6.5.** The representation of the caregiver routes

## 6.3. Managerial Insights and Discussions

HHC services play a significant role in providing care for individuals in the comfort of their homes. As explained in Chapter 2.3, the provision of HHC services has positive effect on patient satisfaction (Vass et al., 2005), improves the quality of living which helps to improve recovery time of patients (Owen et al., 2015), and prevents hospitalization of elderly people with the improvements on the physical and mental conditions (Tomita et al., 2010). Furthermore, several studies show the HHC services are cost effective compared to institutional care (Soderstrom et al., 1999; Anttila et al., 2000; Miller et al., 2005; Hammar et al., 2009; O’Dell and Wheeler, 2012).

However, the HHC facilities face several challenges, including the delivery of high-quality services to patients, ensuring caregiver job satisfaction, optimizing caregiver routes and schedules, reducing both operational costs and environmental footprints. The development and implementation of a DSS, when combined with a scheduling and routing optimization algorithm, present promising solutions to these challenges.

Several studies in the literature have proposed a decision support system to assist HHC centers. For instance, Eveborn et al. (2006) introduced a decision support system, known as LAPS-CARE, for a Swedish HHC. While it is mentioned that the DSS is coded in C, the specific details of its functionality are not provided. Kandakoglu et al. (2020) developed a HHDSS for a division of The Ottawa Hospital. The HHDSS is implemented in Java and uses open-source libraries. The MILP model is utilized to find the schedules of caregivers. However, the model is solved by the commercial solver Gurobi Optimizer. The HHDSS developed in this study is implemented in Python and uses open-source libraries. In addition, to avoid additional software costs, the ALNS-VS algorithm is used to solve the problem.

Healthcare organizations must find ways to deliver high-quality services while minimizing operational costs. This involves cost-effective resource allocation, efficient route planning, and minimizing administrative expenses. However, many HHC centers lack dedicated operations research specialists who can provide daily scheduling and routing plans. As a result, they often experience inefficient resource utilization and costly schedules and routes. According to a National Association for Home Care & Hospice (NAHC, 2015), caregivers in the United States traveled nearly 8 billion miles in 2013, showing a significant increase from 4.76 billion miles in 2006. In addition, caregivers in Norway spend an average of 22% of their working hours in vehicles, which is considered non-value-added time (Holm and Angelsen, 2014). Thus, the implementation of efficient solutions to the HHSRP can result in substantial cost savings for institutions and increase patients' satisfaction. For instance, Kandakoglu et al. (2020) states that the use of HHDSS resulted in a 33% decrease in average total travel time. This led to potential an estimated annual cost reduction of around 100,000 Canadian dollars just for the dialysis division. Both exact solution algorithms which prioritize to find the optimal solutions at the cost of the computational time, and heuristic algorithms, that aim to find near-optimal solutions in short amount of time, can significantly improve the manual scheduling and routing plans of caregivers.

Furthermore, the manual planning of daily schedules and routes is extremely time-consuming task, taking several hours and many staff members to complete (Kandakoglu et al., 2020). Efficient planning reduces resource consumption since it spares the need for involving all staff members in last-minute changes, enabling them to depart from the office earlier to initiate their visits (Eveborn et al., 2006). As demonstrated in Chapter 5.4, CPLEX fails to find optimal solutions for instances with 10 patients and 4 caregivers within the allocated 6 hours. In contrast, the proposed algorithm consistently provides near optimal solutions in less than 2 minutes on average even for larger instances, which consist of 100 patients and 12 caregivers. The proposed algorithm, integrated into a decision support system as its framework is explained in Chapter 6, successfully addresses this challenging task and provides efficient and accurate solutions in a short amount of time.

As discussed in the Chapter 5, the proposed vehicle sharing policy and the solution algorithm provide efficient scheduling and routing plans for HHC centers in short amount of time by using less resources than the standard models in the literature. Vehicle sharing policies allow for better utilization of available vehicles. Instead of each caregiver having a dedicated vehicle, shared vehicles can be used more efficiently, therefore reducing the overall number of vehicles needed. One of the most substantial financial investments in the HHC systems is associated with the number of vehicles employed. Vehicle sharing not only optimizes the allocation of vehicles but also reduces the overall quantity required, thus providing significant savings in both initial investment and operational costs.

An often overlooked advantage is the significance of storing all data within a system. Although it involves extensive data entry, it also allows for data validation and enables the planner to identify operational imbalances. For instance, situations in which one caregiver is responsible for an excessive number of patients become highly evident through the graphical representations (Eveborn et al., 2006).

Furthermore, reducing the environmental footprint of service provision is increasingly important in the context of broader sustainability goals. This includes minimizing fuel consumption, carbon emissions, and energy usage in service delivery. Due to the risks associated with global climate change, governments impose carbon emission taxes on industries with high carbon emission as a tool to mitigate them (Zhang et al., 2015). According to the Pretis (2022), the current carbon taxes, being too low to be effective on reduction of carbon emissions, may lead to future tax increases. An inherent advantage of the proposed vehicle sharing policies is its significant contribution to reducing carbon emissions and decreased environmental impacts. Vehicle sharing results in a reduced fleet size which lowers fuel consumption and emissions. This aligns with the increasing emphasis on sustainability and environmentally friendly practices.

In addition, through optimized or improved scheduling and routing plans, caregivers can also spend more time with patients, allowing them to focus on their healthcare needs rather than struggling with logistics challenges. This focus on enhancing patient care is especially important within the context of HHC, as discussed in Chapter 2.3, given that a significant portion of healthcare service recipients are elderly individuals. Additionally, the provision of efficient plans, in terms of the total working time of caregivers results in increasing number of patients that are served on a daily basis. This allows for the satisfaction of a larger number of patients overall.

# CHAPTER 7
# CONCLUSIONS AND FUTURE RESEARCH

The main contribution of this study is to present a new generic problem to the literature of Workforce Scheduling and Routing Problem (WSRP). This problem introduces two distinct features. First, multiple independent workers can travel in a single shared vehicle. Second, a worker in a vehicle can be dropped off at a customer's location and then picked up by the same vehicle. Although the generic WSRP we introduced in this study can be applied in any field such as telecom, public utilities, or maintenance, we have defined it specifically in the context of the home healthcare industry. Hence, the problem is called Home Healthcare Scheduling and Routing Problem (HHSRP) with Vehicle Sharing (VS) and drop-off and pick-up (DP) policy. The objective of this HHSRP-VS is to minimize caregivers' total flow time and the penalty cost of unvisited patients.

We developed MILP model of this problem using a two-layer approach to easily adapt the DP policy and avoid sub-tour elimination constraints. Since the complexity of the HHSRP-VS can be considered NP-Hard, we proposed a constructive matheuristic upper-bound algorithm (UBA) and an Adaptive Large Neighborhood Search (ALNS) algorithm with problem-specific local search heuristics to solve HHSRP-VS. We generated various problem instances based on some problem features such as the radius of the service area, the number of patients in an area, the patients' demand distribution of the difficulty of care. We then studied on four research questions.

i. We proposed two variations of the caregiver swap heuristic for the ALNS-VS algorithm, called the "common" and "unique" visibility heuristics. Statistical analysis showed no significant difference between these visibility heuristics.

ii. We analyzed the effectiveness of the proposed UBA and ALNS-VS algorithms. The CPLEX solver could only provide integer solutions for 10-patient instances with an average optimality gap of 40.7% in six hours. For the same instances, UBA developed 16.4% worse solutions than CPLEX in less than 1 seconds. However, the ALNS-VS presented a maximum of 19.7% and an average of 6% lower total flow time than the CPLEX solutions only in 1.8 seconds on average. Because of the lack of CPLEX solutions for the problems with more than 10 patients, we compared ALNS-VS solutions with UBA+DP solutions obtained by applying the proposed DP local search heuristic to UBA solutions. The ALNS-VS solutions presented 13.1%, 13.6% and 19.3% and 15.9% lower total flow time than UBA+DP in 1.9, 23, 34 and 119 seconds on average for 10-, 30-, 50- and 100-patient instances, respectively. While ALNS-VS did not result in any unvisited patients, there were 12 instances in UBA+DP where an average of 2 patients were not visited. We concluded that the proposed ALNS-VS algorithm offers both effective and efficient solutions for HHSRP-VS due to its solution qualities and short computation time.

iii. We investigated the effect of DP policy on the total flow time. For this purpose, we presented the HHSRP-M problem that allows vehicle sharing but DP. We first proved that the optimal solutions of the HHSRP-VS are always better than or equal to those in HHSRP-M. Next, in an empirical analysis, we also revealed that the DP policy saves up to 25% in total flow time. We also showed statistically that savings increase as service area gets smaller and patients need more difficult service.

iv. The effects of vehicle sharing with DP policy on total flow time and total service cost were analyzed. For this purpose, we presented the HHSRP-STD problem, which requires each caregiver to travel with their own vehicle, as in the conventional HHSRP. We proved that the optimal flow time of HHSRP-STD is always shorter than that of HHSRP-M, except in the best-case scenario. Next, we conducted an empirical break-even analysis to investigate under what conditions HHSRP-VS could reduce the total cost of service, including hourly vehicle ownership and labor costs. We explored that the denser the area, the higher the chance to reduce cost with the DP policy. Moreover, the possibility of reducing the cost of service by HHSRP-VS increases when the demand for difficult care increases.

Furthermore, a prototype of a HHDSS has been developed to demonstrate the practical application of the proposed ALNS-VS algorithm in solving real-world problems with real geographic road distances. To illustrate this, we tackled the task of visiting COVID-19 patients at their homes for testing and care, a task performed by healthcare providers of the Turkish Ministry of Health during the contact tracing process. Our study focused on identifying susceptible COVID-19 patients in two randomly selected neighboring districts of each of Turkey's three major cities: Ankara, Istanbul, and Izmir. To pinpoint patient locations, we utilized the heat map data available in the mobile application 'Life Fits into Home,' which is developed by the Turkish Ministry of Health. The proposed ALNS-VS algorithm was put into practice to determine an optimal sequence for visiting patients, taking into account actual road distances and utilizing visualization modules.

The proposed HHDSS combined with the ALNS-VS algorithm can significantly enhance the planning and scheduling process of HHC centers in several ways. One of the most significant improvements is observed in the optimized daily plans. As reported by Kandakoglu et al. (2020) with the assistance of effective solution algorithms, HHDSSs can lead to a %30 of reduction in total working time of caregivers. This translates to the hundreds of thousand dollars in savings for a single division. Besides cost saving, when caregivers spend less time traveling, they can visit more patients and allocate more time to patient care. It is obvious that meeting customer needs is the most important element in every service sector. However, its significance is further emphasized within the healthcare sector, particularly in the context of HHC. Furthermore, with the proposed vehicle sharing policy, the required total number of vehicles can also be significantly reduced. This, in turn, can effectively lower both the total investment costs and the total operational costs for HHC businesses. As a result, with fewer vehicles and reduced travel distances, carbon emissions can also be decreased, leading to a cleaner, more environmentally friendly solutions.

As it is discussed in the previous Chapter 6.3, the HHDSS also provides a storage of comprehensive data related to patients, caregivers, and vehicles within the HHDSS is a valuable aspect of the system. This comprehensive data storage allows for robust analysis, prediction, and informed decision-making. The HHDSS stores patient details, including medical history, care requirements, and appointment schedules. Planners can analyze this data to understand patient trends and anticipate future needs. Anticipating future patient needs and ensuring timely visits contribute to better patient care and satisfaction. This insight is vital for capacity planning and resource allocation. Information about caregivers, their qualifications, availability, and workload are recorded in the system. This data enables planners to assess workforce capacity and skill distribution. Details of the vehicles used for patient visits, including fuel efficiency and maintenance schedules, are maintained. This information aids in vehicle allocation and routing optimization. Based on the workforce capacity and expected patient demand, the system can forecast the number of vehicles and caregivers required. This helps in proactively addressing staffing and vehicle fleet needs.

Finally, in dynamic environments, HHDSS combined with optimization algorithms can adapt to changing conditions in real-time such as patient needs, caregiver availability, and unforeseen events. For instance, in traffic management, they can dynamically adjust routes based on traffic conditions. They can also assist in risk assessment and management by identifying potential issues and suggesting strategies to mitigate them. This real-time adaptability results in more efficient resource usage and reduces operational bottlenecks, further contributing to sustainability. Organizations that leverage DSS and optimization algorithms can gain a competitive edge by offering superior service, reducing costs, and responding more effectively to changing market conditions.

The results and insights of this study were obtained under various assumptions. First, we assume that the number of caregivers assigned to a vehicle is fixed and 2. In practice, however, more than two or varying numbers of caregivers can be assigned to vehicles. Because our assumption is restrictive, this kind of flexibility can increase the likelihood of reducing total flow time with the vehicle sharing and DP policies. Therefore, we believe that relaxing this assumption could create new challenging problems and opportunities in HHSRP-VS. Second, the current model mandates that the caregiver be picked up by the same vehicle after being dropped off. Once this assumption is relaxed and caregivers are allowed to travel in any vehicle, the likelihood of lower total flow times may be very high. Third, researchers can also include multiple HHC centers in the problem to develop more centralized decisions, reduce flow time, and increase patient satisfaction. Hence, the new generic problem introduced, and insights developed in this study seem to have the potential to open up new discussions and challenging problems not only in the WSRP literature but also in the vehicle routing problems.

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# APPENDIX A – Computational Results

**Table A.1**. The best-found CPLEX solutions for 10-patient instances and their comparisons with the UBA.

| | CPLEX | | UBA | | | | CPLEX | | UBA | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **UB*** | **GAP (%)** | **UB**** | **CPU** | **% Imp.** | **Instance** | **UB*** | **GAP (%)** | **UB**** | **CPU** | **% Imp.** |
| h10_0_0 | 258.5 | 39 | 335.1 | 0.11 | 22.9 | h30_0_0 | 506.5 | 49.2 | 557.4 | 0.05 | 9.1 |
| h10_0_1 | 256.3 | 35.5 | 341.4 | 0.05 | 24.9 | h30_0_1 | 531.9 | 46.9 | 614.9 | 0.03 | 13.5 |
| h10_0_2 | 248.5 | 30.5 | 338.3 | 0.06 | 26.5 | h30_0_2 | 503.5 | 34.6 | 533.9 | 0.03 | 5.7 |
| h10_0_3 | 255.8 | 38.6 | 343.9 | 0.05 | 25.6 | h30_0_3 | 522.2 | 52.4 | 580.4 | 0.03 | 10.0 |
| h10_0_4 | 233.8 | 29.1 | 318.3 | 0.03 | 26.5 | h30_0_4 | *NA* | *NA* | 514.2 | 0.03 | *NA* |
| h10_1_0 | 258.1 | 30.1 | 379.1 | 0.04 | 31.9 | h30_1_0 | 550.5 | 50.6 | 601.4 | 0.02 | 8.5 |
| h10_1_1 | 288.8 | 35.7 | 385.4 | 0.05 | 25.1 | h30_1_1 | 554.4 | 44.4 | 658.9 | 0.02 | 15.9 |
| h10_1_2 | 267.7 | 27 | 382.3 | 0.04 | 30.0 | h30_1_2 | 533.2 | 34.8 | 577.9 | 0.03 | 7.7 |
| h10_1_3 | 278.2 | 35.6 | 387.9 | 0.04 | 28.3 | h30_1_3 | 522.7 | 48.7 | 624.4 | 0.07 | 16.3 |
| h10_1_4 | 255.4 | 26.1 | 362.3 | 0.03 | 29.5 | h30_1_4 | 483.6 | 38.9 | 558.2 | 0.03 | 13.4 |
| h10_2_0 | 299.3 | 29.5 | 431.1 | 0.03 | 30.6 | h30_2_0 | 628.9 | 52 | 638.6 | 0.04 | 1.5 |
| h10_2_1 | 307.8 | 29.2 | 447.4 | 0.03 | 31.2 | h30_2_1 | 629.6 | 48.2 | 720.9 | 0.09 | 12.7 |
| h10_2_2 | 281.8 | 19.6 | 444.3 | 0.03 | 36.6 | h30_2_2 | 580 | 38.4 | 639.9 | 0.05 | 9.4 |
| h10_2_3 | 308 | 29.9 | 449.9 | 0.03 | 31.5 | h30_2_3 | 576.2 | 48 | 686.4 | 0.10 | 16.1 |
| h10_2_4 | 295.1 | 25.9 | 424.3 | 0.03 | 30.4 | h30_2_4 | *NA* | *NA* | 620.2 | 0.06 | *NA* |
| h20_0_0 | 399.9 | 47.9 | 446.8 | 0.03 | 10.5 | h40_0_0 | 567.4 | 45.4 | 668.6 | 0.02 | 15.1 |
| h20_0_1 | 403 | 45.2 | 469.1 | 0.03 | 14.1 | h40_0_1 | 644.7 | 43.7 | 728.2 | 0.08 | 11.5 |
| h20_0_2 | 378.4 | 38.1 | 452.7 | 0.06 | 16.4 | h40_0_2 | 614.7 | 39.7 | 637.0 | 0.06 | 3.5 |
| h20_0_3 | 390.4 | 49 | 457.7 | 0.22 | 14.7 | h40_0_3 | 646.7 | 49.7 | 698.6 | 0.14 | 7.4 |
| h20_0_4 | 418.6 | 48.1 | 418.7 | 0.03 | 0.0 | h40_0_4 | *NA* | *NA* | 608.7 | 0.03 | *NA* |
| h20_1_0 | 404.4 | 42.2 | 490.8 | 0.03 | 17.6 | h40_1_0 | 621 | 47.7 | 712.6 | 0.03 | 12.9 |
| h20_1_1 | 412.1 | 41.9 | 513.1 | 0.03 | 19.7 | h40_1_1 | 684.4 | 47.2 | 772.2 | 0.02 | 11.4 |
| h20_1_2 | 395 | 44 | 476.0 | 0.03 | 17.0 | h40_1_2 | 676.3 | 40.3 | 681.0 | 0.05 | 0.7 |
| h20_1_3 | 398.1 | 39.9 | 501.7 | 0.04 | 20.6 | h40_1_3 | 660.8 | 49.4 | 742.6 | 0.10 | 11.0 |
| h20_1_4 | *NA* | *NA* | 462.7 | 0.03 | *NA* | h40_1_4 | 652.6 | 47.2 | 652.7 | 0.05 | 0.0 |
| h20_2_0 | 465.6 | 45.2 | 535.6 | 0.03 | 13.1 | h40_2_0 | 708.7 | 50.3 | 741.5 | 0.03 | 4.4 |
| h20_2_1 | 466.4 | 43.2 | 575.1 | 0.02 | 18.9 | h40_2_1 | 745.2 | 47 | 834.2 | 0.02 | 10.7 |
| h20_2_2 | 445.8 | 37.1 | 558.7 | 0.02 | 20.2 | h40_2_2 | 708.6 | 39.6 | 743.0 | 0.03 | 4.6 |
| h20_2_3 | 451 | 44.1 | 563.7 | 0.04 | 20.0 | h40_2_3 | 687.7 | 48.1 | 804.6 | 0.07 | 14.5 |
| h20_2_4 | 384.1 | 29.7 | 524.7 | 0.03 | 26.8 | h40_2_4 | 637.8 | 41.2 | 714.7 | 0.02 | 10.8 |
| *Best-found integer: The best objective function values of the best-found integer solutions by CPLEX. | | | | | | | | | | | |
| **UB: the objective function values of the solutions obtained by the proposed UBA. | | | | | | | | | | | |

**Table A. 2.** The ALNS-VS solutions and their comparisons with CPLEX solutions for 10-patient instances.

| Instance | Best-found | Avg. | #DP | CPU | % Imp. | Instance | Best-found | Avg. | #DP | CPU | % Imp. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| h10_0_0 | 240.5 | 246.3 | 5.4 | 1.7 | 6.9 | h30_0_0 | 452.5 | 468.5 | 2.0 | 2.0 | 10.7 |
| h10_0_1 | 254.3 | 256.4 | 5.2 | 1.8 | 0.8 | h30_0_1 | 527.3 | 527.3 | 2.0 | 1.8 | 0.9 |
| h10_0_2 | 231.0 | 231.8 | 6.0 | 2.0 | 7.0 | h30_0_2 | 500.3 | 500.3 | 2.0 | 1.7 | 0.6 |
| h10_0_3 | 255.8 | 261.0 | 4.4 | 1.8 | 0.0 | h30_0_3 | 504.6 | 504.6 | 3.0 | 1.7 | 3.4 |
| h10_0_4 | 217.2 | 221.4 | 4.4 | 1.6 | 7.1 | h30_0_4 | 449.0 | 451.3 | 2.4 | 1.6 | *NA* |
| h10_1_0 | 252.4 | 257.5 | 6.2 | 1.9 | 2.2 | h30_1_0 | 496.3 | 515.3 | 3.8 | 2.0 | 9.9 |
| h10_1_1 | 282.0 | 283.3 | 5.4 | 1.7 | 2.4 | h30_1_1 | 544.6 | 544.6 | 4.0 | 1.7 | 1.8 |
| h10_1_2 | 243.0 | 245.4 | 7.0 | 1.9 | 9.2 | h30_1_2 | 535.1 | 549.2 | 4.4 | 1.8 | -0.4 |
| h10_1_3 | 272.0 | 275.9 | 6.2 | 1.8 | 2.2 | h30_1_3 | 527.8 | 527.8 | 3.0 | 1.8 | -1.0 |
| h10_1_4 | 235.8 | 238.8 | 6.0 | 1.7 | 7.7 | h30_1_4 | 484.2 | 484.2 | 4.2 | 1.7 | -0.1 |
| h10_2_0 | 278.0 | 287.9 | 6.8 | 1.9 | 7.1 | h30_2_0 | 504.8 | 531.8 | 3.6 | 1.9 | 19.7 |
| h10_2_1 | 305.3 | 308.0 | 6.8 | 1.8 | 0.8 | h30_2_1 | 548.5 | 598.4 | 3.4 | 1.7 | 12.9 |
| h10_2_2 | 276.6 | 277.3 | 6.0 | 1.8 | 1.9 | h30_2_2 | 577.6 | 578.9 | 3.2 | 1.7 | 0.4 |
| h10_2_3 | 303.2 | 306.3 | 4.8 | 1.8 | 1.6 | h30_2_3 | 548.7 | 551.4 | 4.0 | 2.0 | 4.8 |
| h10_2_4 | 279.2 | 282.9 | 5.0 | 1.6 | 5.4 | h30_2_4 | 496.1 | 496.1 | 4.0 | 1.6 | *NA* |
| h20_0_0 | 361.2 | 378.7 | 2.8 | 1.9 | 9.7 | h40_0_0 | 542.6 | 562.3 | 2.0 | 1.9 | 4.4 |
| h20_0_1 | 401.0 | 401.0 | 4.0 | 1.8 | 0.5 | h40_0_1 | 588.4 | 633.4 | 2.0 | 1.9 | 8.7 |
| h20_0_2 | 346.7 | 372.3 | 2.6 | 1.7 | 8.4 | h40_0_2 | 539.1 | 591.4 | 1.0 | 1.7 | 12.3 |
| h20_0_3 | 384.5 | 384.5 | 3.2 | 1.8 | 1.5 | h40_0_3 | 619.2 | 619.2 | 3.0 | 1.8 | 4.2 |
| h20_0_4 | 339.5 | 339.5 | 4.0 | 1.7 | 18.9 | h40_0_4 | 551.8 | 551.8 | 2.0 | 1.6 | *NA* |
| h20_1_0 | 357.1 | 377.2 | 5.4 | 2.0 | 11.7 | h40_1_0 | 593.3 | 620.0 | 3.0 | 1.9 | 4.5 |
| h20_1_1 | 413.1 | 413.2 | 3.6 | 1.8 | -0.2 | h40_1_1 | 665.4 | 668.6 | 4.4 | 1.7 | 2.8 |
| h20_1_2 | 357.4 | 385.4 | 6.0 | 1.9 | 9.5 | h40_1_2 | 606.2 | 649.8 | 1.8 | 1.7 | 10.4 |
| h20_1_3 | 397.7 | 398.0 | 4.2 | 1.7 | 0.1 | h40_1_3 | 650.3 | 650.3 | 3.0 | 1.9 | 1.6 |
| h20_1_4 | 356.8 | 356.8 | 5.6 | 1.6 | *NA* | h40_1_4 | 600.5 | 600.5 | 2.8 | 1.6 | 8.0 |
| h20_2_0 | 409.0 | 438.0 | 4.4 | 1.9 | 12.1 | h40_2_0 | 601.5 | 632.5 | 3.0 | 2.0 | 15.1 |
| h20_2_1 | 428.7 | 460.9 | 4.8 | 1.7 | 8.1 | h40_2_1 | 663.9 | 731.0 | 3.0 | 1.8 | 10.9 |
| h20_2_2 | 374.0 | 424.4 | 3.0 | 1.8 | 16.1 | h40_2_2 | 608.2 | 676.7 | 2.0 | 1.8 | 14.2 |
| h20_2_3 | 433.7 | 435.7 | 4.0 | 2.0 | 3.8 | h40_2_3 | 666.2 | 668.4 | 3.6 | 2.1 | 3.1 |
| h20_2_4 | 380.6 | 387.3 | 4.0 | 1.7 | 0.9 | h40_2_4 | 600.7 | 604.7 | 4.2 | 1.7 | 5.8 |

**Table A.3.** The aggregated results of ALNS-VS, UBA, ALNS_M, ALNS-STD and their comparisons.

| Instance | UBA+DP | ALNS-VS | ALNS-M | ALNS-STD | UBA+DP-UBA (%) | VS-UBA+DP (%) | VS-M (%) | STD-VS (%) | $BER$ |
|---|---|---|---|---|---|---|---|---|---|
| h10_10_0 | 296.5 | 239.98 | 329.18 | 176.67 | 11.6 | 18.9 | 27.2 | 26.0 | 1.2 |
| h10_10_1 | 305.3 | 258.16 | 373.18 | 198.52 | 19.6 | 15.8 | 31.2 | 22.4 | 0.9 |
| h10_10_2 | 371.6 | 289.65 | 435.18 | 229.52 | 15.5 | 21.9 | 33.7 | 20.3 | 0.7 |
| h10_20_0 | 414.5 | 373.16 | 434.10 | 239.80 | 7.7 | 11.4 | 15.6 | 34.3 | 2.4 |
| h10_20_1 | 438.3 | 387.68 | 478.10 | 261.80 | 10.4 | 14.0 | 21.3 | 30.2 | 1.7 |
| h10_20_2 | 479.7 | 431.68 | 540.10 | 293.14 | 13.0 | 15.5 | 25.0 | 27.4 | 1.3 |
| h10_30_0 | 534.9 | 490.83 | 540.08 | 304.79 | 4.6 | 8.8 | 9.9 | 37.2 | 3.2 |
| h10_30_1 | 567.5 | 526.23 | 584.08 | 326.79 | 6.1 | 8.5 | 11.4 | 36.8 | 2.9 |
| h10_30_2 | 595.7 | 553.69 | 646.08 | 357.79 | 9.9 | 10.0 | 17.2 | 32.9 | 2.1 |
| h10_40_0 | 645.6 | 599.49 | 645.62 | 368.88 | 3.4 | 11.8 | 11.9 | 34.9 | 2.6 |
| h10_40_1 | 689.0 | 641.80 | 689.62 | 391.43 | 3.3 | 9.3 | 9.6 | 37.1 | 3.0 |
| h10_40_2 | 711.5 | 670.93 | 751.62 | 421.88 | 7.4 | 11.5 | 16.4 | 32.7 | 2.0 |
| h30_10_0 | 683.1 | 560.65 | 859.66 | 459.52 | 22.1 | 17.8 | 34.8 | 18.0 | 0.6 |
| h30_10_1 | 730.8 | 603.58 | 941.66 | 501.36 | 23.9 | 17.3 | 35.9 | 16.9 | 0.5 |
| h30_10_2 | 860.0 | 665.52 | 1091.79 | 573.90 | 22.2 | 22.3 | 39.0 | 13.8 | 0.4 |
| h30_20_0 | 898.5 | 785.82 | 1030.83 | 569.02 | 15.0 | 12.5 | 23.8 | 27.6 | 1.2 |
| h30_20_1 | 947.4 | 817.17 | 1119.01 | 609.38 | 16.2 | 13.7 | 27.0 | 25.4 | 1.0 |
| h30_20_2 | 1053.3 | 885.24 | 1265.90 | 684.17 | 17.9 | 15.9 | 30.1 | 22.7 | 0.8 |
| h30_30_0 | 1106.4 | 1001.70 | 1202.96 | 676.04 | 9.5 | 9.5 | 16.7 | 32.5 | 1.9 |
| h30_30_1 | 1169.7 | 1040.87 | 1287.13 | 719.03 | 10.5 | 10.9 | 19.1 | 30.9 | 1.6 |
| h30_30_2 | 1272.1 | 1101.78 | 1434.96 | 789.51 | 13.3 | 13.3 | 23.2 | 28.3 | 1.3 |
| h30_40_0 | 1323.2 | 1211.49 | 1380.25 | 789.16 | 6.3 | 8.4 | 12.2 | 34.9 | 2.3 |
| h30_40_1 | 1402.3 | 1259.11 | 1466.82 | 829.19 | 7.4 | 9.9 | 14.2 | 34.1 | 2.2 |
| h30_40_2 | 1492.1 | 1322.80 | 1613.96 | 904.68 | 11.4 | 11.2 | 18.0 | 31.6 | 1.7 |
| h50_10_0 | 1123.8 | 917.19 | 1362.34 | 741.10 | 19.6 | 18.3 | 32.7 | 19.2 | 0.6 |
| h50_10_1 | 1339.2 | 1049.48 | 1634.19 | 878.71 | 20.0 | 21.5 | 35.8 | 16.3 | 0.5 |
| h50_10_2 | 1538.8 | 1207.55 | 1941.84 | 1030.20 | 22.2 | 21.4 | 37.8 | 14.7 | 0.4 |
| h50_20_0 | 1490.6 | 1265.13 | 1617.41 | 928.82 | 11.6 | 15.1 | 21.8 | 26.6 | 1.1 |
| h50_20_1 | 1711.2 | 1394.07 | 1890.92 | 1065.76 | 12.6 | 18.5 | 26.3 | 23.6 | 0.9 |
| h50_20_2 | 1911.4 | 1558.52 | 2196.37 | 1218.73 | 15.7 | 18.3 | 29.0 | 21.8 | 0.8 |
| h50_30_0 | 1817.2 | 1594.62 | 1875.04 | 1119.60 | 7.7 | 12.1 | 15.0 | 29.8 | 1.5 |
| h50_30_1 | 2031.2 | 1729.75 | 2154.47 | 1255.32 | 9.8 | 14.6 | 19.7 | 27.4 | 1.2 |
| h50_30_2 | 2231.5 | 1890.13 | 2464.78 | 1407.72 | 12.9 | 15.2 | 23.3 | 25.5 | 1.1 |
| h50_40_0 | 2139.7 | 1916.01 | 2138.98 | 1310.78 | 6.1 | 10.4 | 10.4 | 31.6 | 1.7 |
| h50_40_1 | 2756.1 | 2051.53 | 2416.16 | 1446.51 | 6.0 | 20.9 | 15.1 | 29.5 | 1.4 |
| h50_40_2 | 4357.0 | 2256.00 | 2742.02 | 1598.29 | 14.2 | 45.8 | 17.7 | 29.2 | 1.4 |
| h100_10_0 | 2433.3 | 2010.13 | 2870.71 | 1580.91 | 16.9 | 17.3 | 30.0 | 21.4 | 0.8 |
| h100_10_1 | 2879.8 | 2360.71 | 3553.15 | 1920.09 | 20.0 | 18.0 | 33.6 | 18.7 | 0.6 |
| h100_10_2 | 2954.9 | 2464.20 | 3719.20 | 1999.56 | 21.4 | 16.6 | 33.7 | 18.9 | 0.6 |
| h100_20_0 | 3112.4 | 2659.69 | 3389.20 | 1967.69 | 11.1 | 14.5 | 21.5 | 26.0 | 1.1 |
| h100_20_1 | 3632.8 | 3046.90 | 4082.18 | 2308.09 | 13.6 | 16.1 | 25.4 | 24.2 | 0.9 |
| h100_20_2 | 3722.0 | 3141.26 | 4230.52 | 2391.76 | 14.3 | 15.6 | 25.7 | 23.9 | 0.9 |
| h100_30_0 | 3751.3 | 3300.48 | 3909.16 | 2366.60 | 7.2 | 12.0 | 15.6 | 28.3 | 1.3 |
| h100_30_1 | 4183.6 | 3677.09 | 4604.94 | 2702.44 | 11.2 | 12.1 | 20.1 | 26.5 | 1.1 |
| h100_30_2 | 4352.5 | 3783.61 | 4783.56 | 2782.05 | 10.5 | 13.0 | 20.9 | 26.5 | 1.1 |
| h100_40_0 | 4391.1 | 3968.25 | 4429.90 | 2755.97 | 4.8 | 9.6 | 10.4 | 30.5 | 1.6 |
| h100_40_1 | 5493.3 | 4400.96 | 5192.64 | 3106.26 | 11.6 | 19.1 | 15.2 | 29.4 | 1.4 |
| h100_40_2 | 6349.7 | 4535.37 | 5336.92 | 3173.82 | 10.6 | 27.4 | 15.0 | 30.0 | 1.5 |

# APPENDIX B – Details of the parameter tuning tests

The ANOVA results in Table B.1 indicate that all of the parameters are statistically significant since their p-values are less than 0.05. In addition, update solution iteration ($\omega$) has the greatest effect on the algorithm since it has the largest adjusted sum of square (Adj SS). In addition to the main effects, the two-way interaction of caregiver swap iteration ($\varphi$) and maximum remove parameter ($\xi$) is the only statistically significant interaction that affects the algorithm's output. Hence, we do not only consider the main effects but also $\varphi*\xi$ two-way interaction while determining the optimum setting for the parameters. For this purpose, we analyzed the main effects plot and used Response Optimizer module of Minitab 19. As seen in Figure B.1, the best setting for ($\omega$, $\varphi$, $\xi$, $\rho$) that minimizes the output is (250,150, 0.5, 0.95) when only main effects are considered. However, the result of the Response Optimization suggests a change on the value of $\varphi$ from 150 to 100 resulting that the optimal setting is ($\omega$, $\varphi$, $\xi$, $\rho$) = (250,100, 0.5, 0.95) with a 95% confidence interval of (3,185; 4,935).

**Table B. 4.** ANOVA results for parameter tuning of the ALNS-VS.

| *Source* | *df* | *Adj SS* | *Adj MS* | *F-Value* | *p-Value* |
|---|---|---|---|---|---|
| Model | 1049 | 2955.5 | 2.8174 | 0.66 | 1.000 |
| Linear | 19 | 779.1 | 41.0042 | 9.63 | 0.000 |
| $\omega$ | 5 | 399.3 | 79.8577 | 18.75 | 0.000 |
| $\varphi$ | 6 | 81.3 | 13.5511 | 3.18 | 0.004 |
| $\xi$ | 4 | 74.5 | 18.6208 | 4.37 | 0.002 |
| $\rho$ | 4 | 224.0 | 56.0005 | 13.15 | 0.000 |
| 2-Way Interactions | 134 | 685.1 | 5.1127 | 1.20 | 0.057 |
| $\omega*\varphi$ | 30 | 132.5 | 4.4159 | 1.04 | 0.410 |
| $\omega*\xi$ | 20 | 39.3 | 1.9659 | 0.46 | 0.980 |
| $\omega*\rho$ | 20 | 9.9 | 0.4960 | 0.12 | 1.000 |
| $\varphi*\xi$ | 24 | 382.7 | 15.9467 | 3.74 | 0.000 |
| $\varphi*\rho$ | 24 | 51.2 | 2.1332 | 0.50 | 0.980 |
| $\xi*\rho$ | 16 | 69.5 | 4.3415 | 1.02 | 0.431 |
| 3-Way Interactions | 416 | 877.2 | 2.1086 | 0.50 | 1.000 |
| $\omega*\varphi*\xi$ | 120 | 402.2 | 3.3517 | 0.79 | 0.959 |
| $\omega*\varphi*\rho$ | 120 | 179.6 | 1.4966 | 0.35 | 1.000 |
| $\omega*\xi*\rho$ | 80 | 115.3 | 1.4413 | 0.34 | 1.000 |
| $\varphi*\xi*\rho$ | 96 | 180.1 | 1.8757 | 0.44 | 1.000 |
| 4-Way Interactions | 480 | 614.1 | 1.2794 | 0.30 | 1.000 |
| $\omega*\varphi*\xi*\rho$ | 480 | 614.1 | 1.2794 | 0.30 | 1.000 |
| Error | 19950 | 84952.0 | 4.2582 | | |
| Total | 20999 | 87907.4 | | | |

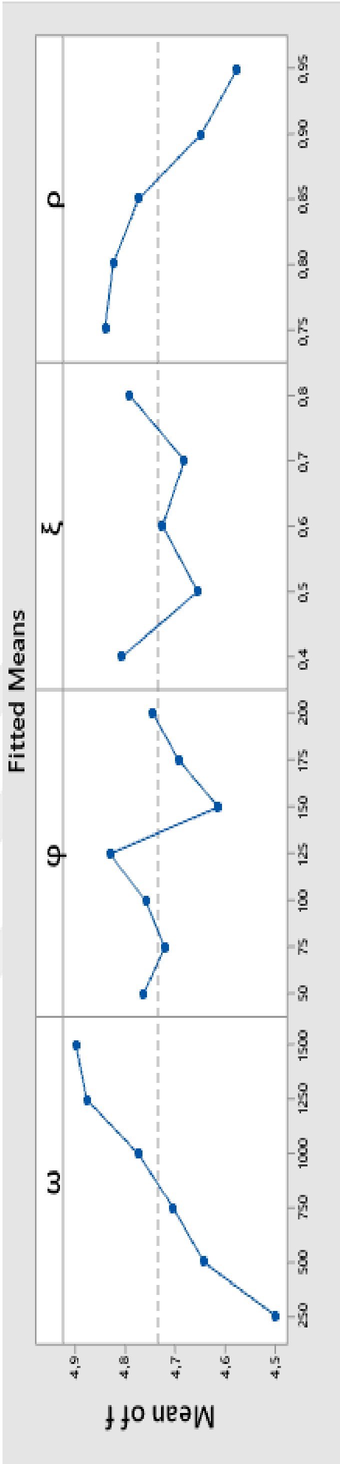


**Figure B.1.** The main effects plot for parameters.

# APPENDIX C – The ALNS-VS solutions: variants of the caregiver swap heuristic

Tables C.1 through C.4 consists of the best-found solutions of the HHSRP problem instances by the variations of the ALNS-VS algorithm for 10, 30, 50 and 100 patients, respectively. These solutions are used in the analyzes in Chapter 5.3, 5.4, 5.5 and 5.6. In the following tables, the “Best-found” and “Avg.” columns indicate the objective values of the best-found and the averages of the best solutions found in five replications, respectively. The column “#DP” shows how many times the caregivers were dropped off. Last, “CPU” presents the computational time of the algorithm in seconds.

**Table C. 5.** The best-found solutions for the instances with 10 patients by the ALNS-VS algorithms.

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Instance | Best-found | Avg. | # DP | CPU | Best-found | Avg. | # DP | CPU | Best-found | Avg. | # DP |
| h10_10_0_0 | 240.54 | 246.304 | 5.2 | 1.94 | 240.54 | 246.304 | 5.2 | 1.85 | 247.48 | 250.056 | 5.00 |
| h10_10_0_1 | 254.28 | 256.42 | 5.2 | 1.78 | 254.28 | 256.42 | 5.2 | 1.77 | 254.28 | 256.328 | 5.2 |
| h10_10_0_2 | 232.1 | 233.628 | 5.8 | 1.87 | 232.1 | 233.628 | 5.8 | 1.89 | 231 | 233.22 | 5.2 |
| h10_10_0_3 | 255.76 | 257.088 | 5.2 | 1.80 | 255.76 | 257.088 | 5.2 | 1.78 | 255.76 | 258.844 | 4.8 |
| h10_10_0_4 | 217.24 | 220.508 | 4.8 | 2.09 | 217.24 | 220.508 | 4.8 | 1.58 | 217.24 | 220.508 | 4.8 |
| h10_10_1_0 | 256.26 | 258.22 | 6 | 1.92 | 256.26 | 258.22 | 6 | 1.85 | 256.26 | 259.148 | 5.8 |
| h10_10_1_1 | 281.98 | 283.932 | 5.4 | 1.77 | 281.98 | 283.932 | 5.4 | 1.74 | 281.98 | 283.848 | 5.6 |
| h10_10_1_2 | 243.04 | 244.848 | 7 | 1.81 | 243.04 | 244.848 | 7 | 1.78 | 245.3 | 245.3 | 7.0 |
| h10_10_1_3 | 271.96 | 275.88 | 6.2 | 1.78 | 271.96 | 275.88 | 6.2 | 1.75 | 276.48 | 277.276 | 5.2 |
| h10_10_1_4 | 237.54 | 241.524 | 6.4 | 1.63 | 237.54 | 241.524 | 6.4 | 1.57 | 235.84 | 240.14 | 5.2 |
| h10_10_2_0 | 278.02 | 290.968 | 7 | 1.74 | 278.02 | 290.968 | 7 | 1.76 | 280.82 | 289.9 | 6.6 |
| h10_10_2_1 | 308.08 | 309.436 | 6.8 | 1.81 | 308.08 | 309.436 | 6.8 | 1.96 | 305.34 | 307.8 | 7.0 |
| h10_10_2_2 | 276.56 | 276.56 | 6 | 1.80 | 276.56 | 276.56 | 6 | 1.87 | 276.56 | 276.56 | 5.6 |
| h10_10_2_3 | 306.36 | 308.12 | 5.2 | 2.00 | 306.36 | 308.12 | 5.2 | 1.88 | 304.76 | 308 | 4.8 |
| h10_10_2_4 | 279.24 | 281.272 | 5.4 | 1.60 | 279.24 | 281.272 | 5.4 | 1.62 | 279.24 | 280.252 | 5.8 |
| h10_20_0_0 | 371.66 | 377.892 | 3.6 | 1.99 | 371.66 | 377.892 | 3.6 | 2.18 | 371.66 | 379.332 | 3.6 |
| h10_20_0_1 | 401.04 | 401.04 | 4 | 1.79 | 401.04 | 401.04 | 4 | 1.74 | 401.04 | 401.416 | 3.8 |
| h10_20_0_2 | 369.14 | 378.356 | 2.8 | 1.82 | 369.14 | 378.356 | 2.8 | 1.99 | 366.94 | 377.916 | 3.2 |
| h10_20_0_3 | 384.52 | 384.52 | 3 | 1.90 | 384.52 | 384.52 | 3 | 1.93 | 384.52 | 384.52 | 3.2 |
| h10_20_0_4 | 339.46 | 339.46 | 4 | 1.72 | 339.46 | 339.46 | 4 | 1.85 | 339.46 | 339.46 | 4.2 |
| h10_20_1_0 | 379.22 | 382.368 | 5.8 | 2.01 | 379.22 | 382.368 | 5.8 | 2.20 | 379.22 | 384.612 | 5.8 |
| h10_20_1_1 | 413.12 | 413.18 | 4.8 | 1.78 | 413.12 | 413.18 | 4.8 | 1.80 | 413.12 | 413.18 | 4.8 |
| h10_20_1_2 | 391.6 | 391.6 | 6 | 1.92 | 391.6 | 391.6 | 6 | 2.12 | 391.6 | 391.6 | 6.0 |
| h10_20_1_3 | 397.7 | 398.096 | 4.6 | 1.85 | 397.7 | 398.096 | 4.6 | 1.92 | 397.7 | 397.964 | 3.8 |
| h10_20_1_4 | 356.78 | 356.78 | 5.2 | 1.66 | 356.78 | 356.78 | 5.2 | 1.80 | 356.78 | 356.78 | 5.2 |
| h10_20_2_0 | 440.16 | 441.372 | 4.8 | 1.92 | 440.16 | 441.372 | 4.8 | 2.18 | 441.22 | 441.948 | 4.6 |
| h10_20_2_1 | 466.62 | 471.716 | 4.8 | 1.72 | 466.62 | 471.716 | 4.8 | 2.07 | 466.62 | 467.172 | 4.6 |
| h10_20_2_2 | 437.02 | 437.048 | 3.2 | 1.79 | 437.02 | 437.048 | 3.2 | 2.34 | 437.02 | 437.076 | 3.4 |
| h10_20_2_3 | 433.98 | 435.724 | 4 | 2.04 | 433.98 | 435.724 | 4 | 2.33 | 433.7 | 437.108 | 3.4 |
| h10_20_2_4 | 380.64 | 386.36 | 5.2 | 1.72 | 380.64 | 386.36 | 5.2 | 1.96 | 380.64 | 385.668 | 5.0 |
| h10_30_0_0 | 472.46 | 472.46 | 2 | 1.92 | 472.46 | 472.46 | 2 | 2.07 | 472.46 | 472.46 | 2.0 |
| h10_30_0_1 | 527.26 | 527.26 | 2 | 1.81 | 527.26 | 527.26 | 2 | 1.95 | 527.26 | 527.26 | 2.0 |
| h10_30_0_2 | 500.28 | 500.28 | 2.2 | 1.77 | 500.28 | 500.28 | 2.2 | 1.83 | 500.28 | 500.28 | 2.0 |
| h10_30_0_3 | 504.56 | 504.56 | 3 | 1.99 | 504.56 | 504.56 | 3 | 2.02 | 504.56 | 504.56 | 3.0 |
| h10_30_0_4 | 449.6 | 452.08 | 2.2 | 1.63 | 449.6 | 452.08 | 2.2 | 1.66 | 449.6 | 452.08 | 2.2 |
| h10_30_1_0 | 519.86 | 519.86 | 4 | 2.08 | 519.86 | 519.86 | 4 | 2.12 | 518.48 | 519.584 | 4.2 |
| h10_30_1_1 | 544.58 | 544.58 | 3.8 | 1.76 | 544.58 | 544.58 | 3.8 | 1.74 | 544.58 | 544.58 | 4.0 |

**Table C.1.** The best-found solutions for the instances with 10 patients by the ALNS-VS algorithms (cont).

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** |
| h10_30_1_3 | 527.82 | 527.82 | 3 | 1.86 | 527.82 | 527.82 | 3 | 1.87 | 527.82 | 527.82 | 3.0 |
| h10_30_1_4 | 484.16 | 484.16 | 4.2 | 1.69 | 484.16 | 484.16 | 4.2 | 1.65 | 484.16 | 484.728 | 3.8 |
| h10_30_2_0 | 538.44 | 538.44 | 4 | 1.90 | 538.44 | 538.44 | 4 | 1.92 | 538.44 | 541.812 | 3.4 |
| h10_30_2_1 | 607.64 | 610.08 | 3.8 | 1.84 | 607.64 | 610.08 | 3.8 | 1.73 | 607.64 | 609.136 | 4.0 |
| h10_30_2_2 | 577.62 | 577.62 | 3 | 1.84 | 577.62 | 577.62 | 3 | 1.86 | 577.62 | 578.624 | 3.2 |
| h10_30_2_3 | 548.68 | 551.352 | 3.8 | 1.97 | 548.68 | 551.352 | 3.8 | 1.97 | 548.68 | 551.352 | 3.8 |
| h10_30_2_4 | 496.08 | 496.08 | 4 | 1.64 | 496.08 | 496.08 | 4 | 1.64 | 496.08 | 496.08 | 3.8 |
| h10_40_0_0 | 567.26 | 567.26 | 2 | 1.79 | 567.26 | 567.26 | 2 | 1.80 | 567.26 | 567.26 | 2.0 |
| h10_40_0_1 | 644.64 | 644.64 | 2 | 2.40 | 644.64 | 644.64 | 2 | 1.80 | 644.64 | 644.64 | 2.0 |
| h10_40_0_2 | 614.5 | 614.5 | 1 | 1.74 | 614.5 | 614.5 | 1 | 1.75 | 614.5 | 614.5 | 1.0 |
| h10_40_0_3 | 619.24 | 619.24 | 3 | 2.00 | 619.24 | 619.24 | 3 | 1.94 | 619.24 | 619.24 | 3.0 |
| h10_40_0_4 | 551.8 | 551.8 | 2 | 1.62 | 551.8 | 551.8 | 2 | 1.60 | 551.8 | 551.8 | 2.0 |
| h10_40_1_0 | 614.74 | 626.04 | 2.8 | 2.61 | 614.74 | 626.04 | 2.8 | 2.01 | 614.74 | 627.808 | 2.6 |
| h10_40_1_1 | 665.44 | 666.496 | 4.8 | 2.02 | 665.44 | 666.496 | 4.8 | 1.75 | 665.44 | 666.496 | 4.8 |
| h10_40_1_2 | 678.02 | 678.02 | 2 | 1.85 | 678.02 | 678.02 | 2 | 1.78 | 678.02 | 678.02 | 2.0 |
| h10_40_1_3 | 650.3 | 650.3 | 3 | 1.91 | 650.3 | 650.3 | 3 | 1.83 | 650.3 | 650.3 | 3.0 |
| h10_40_1_4 | 600.48 | 600.48 | 3 | 1.72 | 600.48 | 600.48 | 3 | 1.57 | 600.48 | 600.48 | 2.8 |
| h10_40_2_0 | 640.18 | 640.18 | 3 | 1.93 | 640.18 | 640.18 | 3 | 1.97 | 640.18 | 640.18 | 3.0 |
| h10_40_2_1 | 743.28 | 743.352 | 3.4 | 1.80 | 743.28 | 743.352 | 3.4 | 1.81 | 743.28 | 743.376 | 3.2 |
| h10_40_2_2 | 704.28 | 705.2 | 2.8 | 1.81 | 704.28 | 705.2 | 2.8 | 1.90 | 704.28 | 704.28 | 3.0 |
| h10_40_2_3 | 666.2 | 668.412 | 4 | 2.10 | 666.2 | 668.412 | 4 | 2.00 | 666.2 | 666.2 | 4.0 |
| h10_40_2_4 | 600.7 | 604.672 | 4.2 | 1.61 | 600.7 | 604.672 | 4.2 | 1.71 | 600.7 | 608.636 | 3.2 |

**Table C. 6.** The best-found solutions for the instances with 30 patients by the ALNS-VS algorithms

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h30_10_0_0 | 548.5 | 563.568 | 17.4 | 24 | 538.76 | 555.344 | 17.6 | 18 | 573.98 | 579.24 |
| h30_10_0_1 | 571.6 | 579.116 | 15.4 | 19 | 568.22 | 577 | 14.6 | 18 | 569.52 | 578.56 |
| h30_10_0_2 | 552.34 | 562.172 | 20 | 13 | 561.66 | 566.736 | 20.6 | 15 | 559.76 | 568.376 |
| h30_10_0_3 | 571.22 | 577.948 | 15.8 | 15 | 576.48 | 577.88 | 16.6 | 21 | 556.06 | 573.336 |
| h30_10_0_4 | 559.58 | 564.284 | 16.2 | 20 | 559.84 | 566.768 | 16.2 | 29 | 558.4 | 573.14 |
| h30_10_1_0 | 604.16 | 622.404 | 17.8 | 15 | 604.16 | 628.3 | 16.8 | 27 | 638.6 | 638.6 |
| h30_10_1_1 | 614.22 | 623.92 | 18.8 | 16 | 614.22 | 622.272 | 18.6 | 34 | 619.96 | 632.488 |
| h30_10_1_2 | 604.38 | 613.864 | 21.6 | 17 | 611.5 | 616.04 | 20.4 | 25 | 610.78 | 614.156 |
| h30_10_1_3 | 597.14 | 600.38 | 17.6 | 22 | 597.14 | 602.984 | 18 | 29 | 595.46 | 604.856 |
| h30_10_1_4 | 597.98 | 604.148 | 19 | 23 | 599.12 | 607.832 | 18.8 | 28 | 601.34 | 609.864 |
| h30_10_2_0 | 664.76 | 678.128 | 16.2 | 29 | 659.7 | 676.34 | 15.8 | 28 | 670.74 | 680.964 |
| h30_10_2_1 | 665.44 | 690.324 | 17.2 | 28 | 663.06 | 681.62 | 18.6 | 29 | 666.94 | 684.94 |
| h30_10_2_2 | 671.58 | 682.828 | 17.4 | 27 | 669.14 | 678.1 | 20.2 | 29 | 675.68 | 680.876 |
| h30_10_2_3 | 652.6 | 664.488 | 17.4 | 29 | 651.54 | 664.096 | 17.8 | 30 | 661.56 | 676.724 |
| h30_10_2_4 | 673.22 | 679.768 | 15.6 | 21 | 663.02 | 677.964 | 15.8 | 22 | 670.54 | 678.972 |
| h30_20_0_0 | 769.9 | 788.924 | 12.4 | 30 | 770.96 | 786.868 | 13.8 | 28 | 765.02 | 774.152 |
| h30_20_0_1 | 795.58 | 810.9 | 14.8 | 32 | 795.58 | 815.54 | 16 | 32 | 800.84 | 803.496 |
| h30_20_0_2 | 818.36 | 836.032 | 14.8 | 28 | 814.02 | 828.084 | 16.4 | 26 | 824.42 | 826.392 |
| h30_20_0_3 | 767.94 | 777.92 | 16 | 30 | 773.48 | 779.252 | 16 | 27 | 768.48 | 778.844 |
| h30_20_0_4 | 777.32 | 779.608 | 16.6 | 27 | 768.92 | 777.264 | 15.8 | 27 | 777.34 | 779.472 |
| h30_20_1_0 | 816.72 | 831.776 | 15.4 | 30 | 818.06 | 832.088 | 16.4 | 34 | 824.16 | 833.692 |

**Table C.2.** The best-found solutions for the instances with 30 patients by the ALNS-VS algorithms (cont.).

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h30_20_1_1 | 866.12 | 880.496 | 14.4 | 30 | 855.12 | 875.128 | 13.4 | 21 | 873.28 | 883.736 |
| h30_20_1_2 | 808.28 | 829.98 | 16 | 25 | 809.8 | 824.556 | 14.4 | 15 | 825.18 | 833.808 |
| h30_20_1_3 | 785.9 | 798.828 | 17.8 | 30 | 796.66 | 802.68 | 16.4 | 18 | 799.96 | 812.512 |
| h30_20_1_4 | 808.82 | 822.028 | 13.4 | 20 | 808.82 | 820.572 | 12.8 | 11 | 823.44 | 824.344 |
| h30_20_2_0 | 874.98 | 890.644 | 14.6 | 37 | 845.38 | 878.92 | 15.8 | 20 | 854.42 | 875.464 |
| h30_20_2_1 | 923.62 | 940.1 | 15.4 | 28 | 905.16 | 936.428 | 14.8 | 17 | 930.2 | 948.36 |
| h30_20_2_2 | 894.72 | 904.356 | 15.8 | 26 | 894.72 | 901.516 | 16 | 15 | 894.72 | 904.348 |
| h30_20_2_3 | 849.02 | 866.828 | 16.6 | 25 | 832.84 | 854.684 | 17 | 16 | 861.08 | 874.564 |
| h30_20_2_4 | 883.88 | 891.828 | 13.4 | 20 | 865.94 | 888 | 14.2 | 10 | 878.08 | 893.408 |
| h30_30_0_0 | 959.54 | 972.352 | 10.2 | 24 | 974.96 | 977.052 | 10 | 15 | 958.58 | 964.776 |
| h30_30_0_1 | 1039.02 | 1044.46 | 8.6 | 15 | 1036.04 | 1044.176 | 10.2 | 15 | 1042.08 | 1044.824 |
| h30_30_0_2 | 1053.54 | 1069.328 | 12.8 | 15 | 1054.2 | 1068.404 | 13.2 | 15 | 1050.98 | 1067.116 |
| h30_30_0_3 | 989.12 | 992.924 | 12.6 | 16 | 969.52 | 986.4 | 13.2 | 15 | 991.5 | 999.876 |
| h30_30_0_4 | 967.3 | 983.896 | 12.6 | 15 | 986.98 | 989.408 | 12.4 | 16 | 986.98 | 993.932 |
| h30_30_1_0 | 1045.36 | 1053.992 | 16 | 16 | 1045.8 | 1055.556 | 16 | 15 | 1046.62 | 1058.228 |
| h30_30_1_1 | 1106.12 | 1112.152 | 11 | 15 | 1081.98 | 1106.804 | 11.2 | 15 | 1088.9 | 1103.64 |
| h30_30_1_2 | 1047.8 | 1064.38 | 15.8 | 16 | 1031.38 | 1056.944 | 15 | 17 | 1051.7 | 1058.096 |
| h30_30_1_3 | 996.64 | 1031.664 | 13.4 | 22 | 998.02 | 1035.208 | 13.2 | 16 | 1037.76 | 1049.976 |
| h30_30_1_4 | 1008.44 | 1011.236 | 12 | 21 | 1014 | 1021.616 | 11 | 10 | 1004.88 | 1020.872 |
| h30_30_2_0 | 1069.3 | 1087.996 | 15.6 | 30 | 1089.06 | 1107.484 | 12.6 | 19 | 1093.58 | 1102.92 |
| h30_30_2_1 | 1163.3 | 1172.428 | 14 | 26 | 1159.6 | 1174.088 | 11.6 | 15 | 1163.86 | 1184.056 |
| h30_30_2_2 | 1144.22 | 1149.812 | 14 | 25 | 1140.68 | 1143.916 | 15 | 16 | 1143.66 | 1147.144 |
| h30_30_2_3 | 1057.34 | 1083.984 | 13.6 | 28 | 1062.86 | 1085.592 | 14.6 | 15 | 1096.34 | 1108.792 |
| h30_30_2_4 | 1074.72 | 1080.016 | 11.6 | 21 | 1074.72 | 1081.74 | 13 | 11 | 1064.38 | 1078.572 |
| h30_40_0_0 | 1163.52 | 1172.112 | 10.6 | 26 | 1163.52 | 1171.192 | 9.6 | 15 | 1164.2 | 1174.66 |
| h30_40_0_1 | 1249.28 | 1249.28 | 7 | 25 | 1246.38 | 1247.368 | 9.2 | 15 | 1246.44 | 1248.508 |
| h30_40_0_2 | 1274.94 | 1283.996 | 7.8 | 25 | 1281.48 | 1287.564 | 8.2 | 15 | 1274.94 | 1281.036 |
| h30_40_0_3 | 1179.64 | 1202.1 | 10.6 | 24 | 1186.42 | 1199.2 | 10.2 | 15 | 1207.42 | 1220.948 |
| h30_40_0_4 | 1190.08 | 1196.688 | 9.2 | 20 | 1190.08 | 1194.176 | 9.2 | 11 | 1190.08 | 1195.7 |
| h30_40_1_0 | 1253.14 | 1261.06 | 10.8 | 25 | 1252.72 | 1266.272 | 9.6 | 14 | 1246.96 | 1261.52 |
| h30_40_1_1 | 1328.04 | 1336.316 | 9.2 | 29 | 1336.52 | 1341 | 9.2 | 15 | 1325.7 | 1332.864 |
| h30_40_1_2 | 1273.12 | 1280.696 | 11.8 | 26 | 1271.72 | 1282.864 | 13.2 | 15 | 1281.36 | 1283.688 |
| h30_40_1_3 | 1224.14 | 1239.648 | 11.6 | 25 | 1225.26 | 1250.016 | 7.8 | 15 | 1264.06 | 1273.464 |
| h30_40_1_4 | 1217.12 | 1221.356 | 8.4 | 21 | 1220.02 | 1223.52 | 8.4 | 10 | 1210.7 | 1224.636 |
| h30_40_2_0 | 1298.9 | 1315.564 | 11.8 | 25 | 1301.42 | 1314.672 | 12 | 15 | 1298.9 | 1303.552 |
| h30_40_2_1 | 1413.4 | 1423.804 | 10.6 | 19 | 1416 | 1436.756 | 10.2 | 15 | 1422.44 | 1425.116 |
| h30_40_2_2 | 1348.32 | 1363.456 | 10.6 | 15 | 1360.74 | 1366.648 | 11 | 15 | 1363.52 | 1370.188 |
| h30_40_2_3 | 1306.24 | 1319.656 | 11.8 | 15 | 1292.98 | 1315.408 | 10.4 | 15 | 1305.46 | 1319.32 |
| h30_40_2_4 | 1247.14 | 1256.468 | 11.4 | 10 | 1245.02 | 1256.672 | 10.2 | 10 | 1247.14 | 1257.02 |

**Table C. 7.** The best-found solutions for the instances with 50 patients by the ALNS-VS algorithms

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h50_10_0_0 | 909.82 | 938.08 | 27.6 | 36 | 925.44 | 943.03 | 28 | 39 | 930.86 | 952.35 |
| h50_10_0_1 | 930.92 | 945.58 | 30 | 32 | 931.62 | 943.52 | 33 | 35.4 | 937.54 | 949.22 |
| h50_10_0_2 | 942.04 | 951.08 | 30.2 | 36 | 940.80 | 951.14 | 30.6 | 39.6 | 932.86 | 954.17 |
| h50_10_0_3 | 889.4 | 909.50 | 28.2 | 32 | 860.06 | 921.51 | 29.2 | 40.2 | 940.48 | 953.92 |
| h50_10_0_4 | 913.76 | 925.07 | 28 | 35 | 927.30 | 931.41 | 27.6 | 34.6 | 910.20 | 919.16 |
| h50_10_1_0 | 1070.26 | 1080.83 | 28.2 | 32 | 1063.70 | 1072.54 | 28.2 | 39 | 1113.02 | 1124.70 |
| h50_10_1_1 | 1072.84 | 1086.14 | 27.8 | 31 | 1089.38 | 1102.11 | 25.2 | 34.2 | 1082.86 | 1094.71 |
| h50_10_1_2 | 1053.3 | 1078.44 | 29 | 33 | 1066.10 | 1098.62 | 29.4 | 33.4 | 1063.92 | 1084.54 |
| h50_10_1_3 | 1021 | 1064.35 | 28.2 | 33 | 1055.60 | 1075.01 | 28.8 | 32 | 1059.56 | 1080.78 |
| h50_10_1_4 | 1030.02 | 1046.45 | 30.8 | 42 | 1019.32 | 1043.08 | 32 | 40.8 | 1027.76 | 1042.82 |
| h50_10_2_0 | 1211.42 | 1240.41 | 28.4 | 47 | 1219.90 | 1234.61 | 28.2 | 42.4 | 1246.84 | 1265.81 |
| h50_10_2_1 | 1219.42 | 1242.99 | 28.4 | 36 | 1216.34 | 1234.95 | 26 | 37.8 | 1228.12 | 1253.67 |
| h50_10_2_2 | 1216.24 | 1244.29 | 31.6 | 36 | 1246.30 | 1257.28 | 28.6 | 34 | 1238.10 | 1258.67 |
| h50_10_2_3 | 1183 | 1219.13 | 27.8 | 31 | 1224.58 | 1233.18 | 27.6 | 38 | 1195.12 | 1228.56 |
| h50_10_2_4 | 1207.66 | 1221.07 | 28.8 | 32 | 1177.94 | 1201.63 | 28.2 | 41.6 | 1203.40 | 1227.23 |
| h50_20_0_0 | 1267.5 | 1290.61 | 24.6 | 39 | 1291.12 | 1295.83 | 25.8 | 34.2 | 1312.28 | 1338.59 |
| h50_20_0_1 | 1299.14 | 1313.87 | 23.8 | 30 | 1314.48 | 1338.43 | 23.8 | 31.4 | 1274.34 | 1306.00 |
| h50_20_0_2 | 1301.56 | 1324.11 | 24.8 | 34 | 1294.10 | 1322.08 | 25.6 | 38.2 | 1316.54 | 1333.51 |
| h50_20_0_3 | 1176.6 | 1194.74 | 28 | 38 | 1188.76 | 1192.50 | 26.6 | 35 | 1187.82 | 1194.77 |
| h50_20_0_4 | 1280.86 | 1310.50 | 23.6 | 32 | 1263.50 | 1284.00 | 23.4 | 35.6 | 1281.60 | 1306.30 |
| h50_20_1_0 | 1406.52 | 1432.50 | 25.2 | 37 | 1404.30 | 1415.00 | 25.6 | 33.6 | 1478.90 | 1492.80 |
| h50_20_1_1 | 1382.12 | 1430.88 | 23.4 | 31 | 1398.40 | 1419.40 | 26 | 35.4 | 1440.70 | 1470.40 |
| h50_20_1_2 | 1465.96 | 1479.76 | 23.2 | 36 | 1468.90 | 1488.20 | 24.8 | 33 | 1446.40 | 1458.00 |
| h50_20_1_3 | 1331.9 | 1347.19 | 25.6 | 30 | 1322.10 | 1352.20 | 26 | 36.2 | 1374.60 | 1386.50 |
| h50_20_1_4 | 1383.84 | 1389.09 | 28.8 | 36 | 1388.80 | 1402.30 | 27.8 | 37.6 | 1373.50 | 1401.60 |
| h50_20_2_0 | 1591.36 | 1609.98 | 26.6 | 34 | 1546.50 | 1598.00 | 28.4 | 41.4 | 1624.20 | 1642.40 |
| h50_20_2_1 | 1588.36 | 1607.17 | 27.4 | 29 | 1557.80 | 1590.50 | 28.2 | 46 | 1585.90 | 1608.30 |
| h50_20_2_2 | 1602.74 | 1638.72 | 27 | 36 | 1575.10 | 1614.20 | 26.4 | 35.2 | 1594.10 | 1620.20 |
| h50_20_2_3 | 1465.66 | 1509.78 | 21.4 | 32 | 1464.00 | 1499.70 | 25 | 33.2 | 1522.40 | 1549.00 |
| h50_20_2_4 | 1544.46 | 1589.41 | 26.8 | 42 | 1592.30 | 1612.00 | 24.6 | 31 | 1573.80 | 1615.10 |
| h50_30_0_0 | 1569.1 | 1599.30 | 19.6 | 35 | 1608.30 | 1624.40 | 21.2 | 35.6 | 1665.60 | 1676.00 |
| h50_30_0_1 | 1598.98 | 1635.80 | 20.8 | 31 | 1639.70 | 1669.40 | 20 | 35.2 | 1652.20 | 1672.10 |
| h50_30_0_2 | 1679.3 | 1688.92 | 19.4 | 30 | 1672.30 | 1693.00 | 21.8 | 42.6 | 1677.00 | 1696.30 |
| h50_30_0_3 | 1504.66 | 1514.45 | 21.4 | 33 | 1449.40 | 1484.80 | 25.2 | 43 | 1496.70 | 1509.10 |
| h50_30_0_4 | 1621.08 | 1648.01 | 20.8 | 36 | 1637.50 | 1655.10 | 18.6 | 31.4 | 1645.20 | 1658.00 |
| h50_30_1_0 | 1723.9 | 1734.77 | 22.2 | 31 | 1696.50 | 1720.30 | 20.4 | 34.4 | 1813.50 | 1844.30 |
| h50_30_1_1 | 1746.08 | 1794.46 | 18.4 | 28 | 1753.20 | 1801.10 | 17.8 | 30.6 | 1803.40 | 1816.20 |
| h50_30_1_2 | 1808.54 | 1835.79 | 21 | 27 | 1800.50 | 1826.20 | 20.6 | 30.6 | 1839.00 | 1859.10 |
| h50_30_1_3 | 1625.76 | 1653.10 | 22.6 | 37 | 1645.00 | 1662.30 | 22 | 33.4 | 1682.70 | 1696.30 |
| h50_30_1_4 | 1744.46 | 1798.96 | 20 | 33 | 1731.00 | 1790.50 | 19 | 31.2 | 1771.50 | 1783.40 |
| h50_30_2_0 | 1836.42 | 1922.96 | 25.2 | 42 | 1923.70 | 1976.20 | 22.4 | 33.4 | 1967.30 | 2025.20 |
| h50_30_2_1 | 1938.74 | 1968.94 | 20 | 30 | 1957.30 | 1963.80 | 22 | 34.6 | 1947.70 | 1961.50 |
| h50_30_2_2 | 1980.06 | 2001.14 | 20.2 | 27 | 1965.10 | 2008.80 | 21.6 | 30.4 | 2023.90 | 2035.70 |
| h50_30_2_3 | 1764.08 | 1803.30 | 23.6 | 38 | 1752.50 | 1805.90 | 22.2 | 35.8 | 1804.60 | 1834.10 |
| h50_30_2_4 | 1931.36 | 1940.23 | 19.4 | 30 | 1931.20 | 1943.40 | 20.4 | 32.4 | 1912.80 | 1936.10 |
| h50_40_0_0 | 1871.68 | 1915.67 | 19 | 51 | 1896.70 | 1931.10 | 17.2 | 30.6 | 2043.00 | 2050.80 |
| h50_40_0_1 | 1971.42 | 2004.05 | 14.2 | 39 | 1958.70 | 2007.60 | 15.4 | 29 | 2032.60 | 2039.20 |
| h50_40_0_2 | 2012.02 | 2070.38 | 15.4 | 42 | 2078.10 | 2097.70 | 15.2 | 36.4 | 2099.40 | 2104.30 |
| h50_40_0_3 | 1774.16 | 1809.53 | 19.2 | 43 | 1773.60 | 1798.10 | 20 | 42.2 | 1801.60 | 1815.30 |
| h50_40_0_4 | 1950.78 | 1969.72 | 12.8 | 29 | 1962.00 | 1980.30 | 15.6 | 37.8 | 1977.00 | 1985.50 |
| h50_40_1_0 | 2047.46 | 2091.54 | 17.6 | 38 | 2021.90 | 2078.50 | 18.8 | 37.6 | 2124.90 | 2159.10 |
| h50_40_1_1 | 2071.16 | 2108.10 | 15 | 32 | 2072.70 | 2113.70 | 17.6 | 36.8 | 2129.40 | 2163.30 |
| h50_40_1_2 | 2144.36 | 2193.98 | 14.8 | 28 | 2130.70 | 2217.70 | 16 | 42.2 | 2239.10 | 2272.80 |
| h50_40_1_3 | 1914.2 | 1936.31 | 16.4 | 31 | 1875.30 | 1916.40 | 22.4 | 45.2 | 1982.60 | 2004.90 |
| h50_40_1_4 | 2080.46 | 2126.72 | 17.4 | 30 | 2071.90 | 2149.20 | 16.4 | 31.2 | 2120.10 | 2137.70 |

**Table C.3.** The best-found solutions for the instances with 50 patients by the ALNS-VS algorithms (cont.)

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h50_40_2_0 | 2287.30 | 2328.43 | 18 | 28 | 2242.9 | 2335.8 | 18.8 | 33.4 | 2393.8 | 2414.1 |
| h50_40_2_1 | 2292.64 | 2326.44 | 16.6 | 31 | 2313.1 | 2334.2 | 17.6 | 33.2 | 2335.0 | 2350.9 |
| h50_40_2_2 | 2352.22 | 2402.03 | 17.4 | 34 | 2353.7 | 2391.2 | 18 | 36.4 | 2404.3 | 2418.8 |
| h50_40_2_3 | 2056.96 | 2139.99 | 18.4 | 30 | 2062.9 | 2097.9 | 19 | 46.4 | 2096.0 | 2137.2 |
| h50_40_2_4 | 2290.88 | 2307.47 | 19.6 | 28 | 2284.7 | 2298.3 | 21.4 | 34.4 | 2291.9 | 2306.4 |

**Table C. 8.** The best-found solutions for the instances with 100 patients by the ALNS-VS algorithms.

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h100_10_0_0 | 1975.94 | 2033.988 | 49.4 | 149.08 | 2019.76 | 2066.468 | 50.4 | 115.4 | 2040.06 | 2064.648 |
| h100_10_0_1 | 2051.56 | 2070.744 | 48.4 | 113.68 | 1964.26 | 2012.772 | 52.4 | 135.6 | 2029.7 | 2067.368 |
| h100_10_0_2 | 2041.64 | 2061.932 | 48.8 | 99.75 | 1977.2 | 2024.948 | 52 | 137 | 1991.1 | 2023.512 |
| h100_10_0_3 | 2013.56 | 2035.148 | 53.8 | 101.77 | 1953.18 | 2035.676 | 49.8 | 117.6 | 2018.1 | 2027.964 |
| h100_10_0_4 | 1967.94 | 2021.876 | 50.6 | 110.50 | 1940.72 | 2018.312 | 52.2 | 142.4 | 2076.9 | 2097.88 |
| h100_10_1_0 | 2382.64 | 2436.08 | 47.4 | 138.95 | 2405.42 | 2453.616 | 49.2 | 126.2 | 2465.1 | 2496.02 |
| h100_10_1_1 | 2326.82 | 2357.72 | 52 | 148.36 | 2352.70 | 2397.42 | 48.8 | 140 | 2328.68 | 2402.86 |
| h100_10_1_2 | 2388.90 | 2449.05 | 47 | 109.69 | 2387.84 | 2407.90 | 49.8 | 112 | 2368.82 | 2393.16 |
| h100_10_1_3 | 2327.80 | 2406.86 | 52.4 | 111.42 | 2393.56 | 2434.27 | 51.6 | 119.6 | 2379.28 | 2411.78 |
| h100_10_1_4 | 2377.38 | 2423.96 | 50 | 121.26 | 2403.40 | 2428.49 | 51.2 | 114 | 2470.76 | 2508.92 |
| h100_10_2_0 | 2492.14 | 2552.20 | 49.4 | 119.28 | 2481.96 | 2560.17 | 51.2 | 123.4 | 2555.28 | 2580.46 |
| h100_10_2_1 | 2413.36 | 2472.93 | 49 | 147.52 | 2455.66 | 2532.70 | 47 | 98.4 | 2464.08 | 2517.13 |
| h100_10_2_2 | 2480.80 | 2532.17 | 49.2 | 110.87 | 2498.76 | 2527.12 | 51.8 | 131.2 | 2501.24 | 2510.07 |
| h100_10_2_3 | 2457.34 | 2489.38 | 52.4 | 144.96 | 2391.60 | 2533.36 | 52.4 | 134.4 | 2516.92 | 2547.64 |
| h100_10_2_4 | 2477.34 | 2517.40 | 53.8 | 146.06 | 2470.08 | 2507.38 | 53 | 121.2 | 2534.56 | 2577.45 |
| h100_20_0_0 | 2657.80 | 2711.22 | 43 | 128.59 | 2614.92 | 2713.10 | 40.8 | 114.4 | 2691.18 | 2707.95 |
| h100_20_0_1 | 2681.96 | 2711.83 | 42.6 | 125.32 | 2662.06 | 2719.92 | 41.2 | 106.4 | 2733.38 | 2774.04 |
| h100_20_0_2 | 2611.18 | 2678.72 | 44.6 | 128.44 | 2690.94 | 2740.40 | 38.8 | 129.6 | 2704.62 | 2726.70 |
| h100_20_0_3 | 2629.60 | 2675.42 | 44 | 105.09 | 2574.78 | 2647.04 | 44.2 | 134.6 | 2667.82 | 2702.70 |
| h100_20_0_4 | 2717.90 | 2769.44 | 42.8 | 122.81 | 2687.62 | 2737.07 | 44.4 | 132.4 | 2850.54 | 2885.18 |
| h100_20_1_0 | 3024.92 | 3068.61 | 45 | 119.07 | 3058.46 | 3090.73 | 44.6 | 114.2 | 2990.66 | 3061.63 |
| h100_20_1_1 | 3003.90 | 3066.52 | 47.2 | 102.61 | 3004.40 | 3065.98 | 44.4 | 123.8 | 3044.90 | 3095.76 |
| h100_20_1_2 | 3036.40 | 3072.89 | 46.4 | 119.15 | 3053.54 | 3081.45 | 47.8 | 144.6 | 3082.14 | 3110.57 |
| h100_20_1_3 | 3078.32 | 3105.32 | 45.8 | 112.63 | 3064.24 | 3097.34 | 47.8 | 148.6 | 3017.06 | 3072.51 |
| h100_20_1_4 | 3090.96 | 3174.91 | 45.8 | 112.93 | 3125.54 | 3168.02 | 48.4 | 101.2 | 3206.98 | 3234.46 |
| h100_20_2_0 | 3175.98 | 3262.40 | 48.8 | 99.51 | 3173.98 | 3253.58 | 49.4 | 130.2 | 3167.02 | 3205.34 |
| h100_20_2_1 | 3134.16 | 3204.64 | 45.8 | 116.13 | 3149.68 | 3165.06 | 46.8 | 131.6 | 3134.74 | 3164.36 |
| h100_20_2_2 | 3139.24 | 3176.72 | 49.4 | 126.49 | 3205.72 | 3244.50 | 46.4 | 121.8 | 3187.52 | 3253.49 |
| h100_20_2_3 | 3082.96 | 3170.28 | 48.6 | 132.11 | 3124.34 | 3199.83 | 48 | 127 | 3150.58 | 3193.79 |
| h100_20_2_4 | 3173.98 | 3233.62 | 48.2 | 137.97 | 3246.96 | 3288.03 | 46 | 110.4 | 3339.36 | 3348.96 |
| h100_30_0_0 | 3273.16 | 3341.56 | 33.2 | 104.89 | 3393.88 | 3426.43 | 33.2 | 113 | 3406.66 | 3452.16 |
| h100_30_0_1 | 3398.24 | 3429.25 | 32.2 | 120.67 | 3276.74 | 3369.55 | 32.2 | 103.2 | 3463.10 | 3488.12 |
| h100_30_0_2 | 3241.28 | 3351.30 | 34.6 | 113.79 | 3364.72 | 3403.68 | 36 | 117.2 | 3364.26 | 3374.55 |
| h100_30_0_3 | 3191.18 | 3266.75 | 36.2 | 101.53 | 3230.68 | 3303.51 | 34.6 | 107 | 3165.96 | 3197.29 |

**Table C.4.** The best-found solutions for the instances with 100 patients by the ALNS-VS algorithms (cont.)

| | ALNS-VS_Unique | | | | ALNS-VS_Common | | | | ALNS-VS_No-Swap | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Instance** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** | **# DP** | **CPU** | **Best-found** | **Avg.** |
| h100_30_0_4 | 3398.52 | 3439.18 | 34.8 | 120.98 | 3383.56 | 3400.45 | 38 | 113.8 | 3504.04 | 3551.21 |
| h100_30_1_0 | 3702.12 | 3782.59 | 41.4 | 139.78 | 3696.76 | 3785.92 | 37.8 | 110.8 | 3808.16 | 3892.71 |
| h100_30_1_1 | 3713.72 | 3778.30 | 33.2 | 110.19 | 3704.40 | 3748.71 | 34 | 97.8 | 3639.32 | 3727.42 |
| h100_30_1_2 | 3647.28 | 3784.80 | 39 | 103.34 | 3630.70 | 3744.15 | 41.4 | 152 | 3808.50 | 3831.99 |
| h100_30_1_3 | 3586.44 | 3688.59 | 39.2 | 103.71 | 3606.88 | 3676.64 | 40 | 142.4 | 3572.16 | 3662.64 |
| h100_30_1_4 | 3735.90 | 3864.74 | 37.2 | 116.17 | 3820.04 | 3888.97 | 35.2 | 96.2 | 3912.46 | 3957.38 |
| h100_30_2_0 | 3875.58 | 3914.14 | 41 | 103.81 | 3825.66 | 3916.22 | 40.8 | 106 | 3908.42 | 3958.00 |
| h100_30_2_1 | 3829.38 | 3873.24 | 39.6 | 92.95 | 3798.62 | 3919.96 | 38.6 | 101.2 | 3851.70 | 3916.98 |
| h100_30_2_2 | 3692.94 | 3874.69 | 40 | 113 | 3895.78 | 3997.08 | 37.8 | 91.2 | 3835.20 | 3894.89 |
| h100_30_2_3 | 3736.70 | 3766.84 | 43.8 | 155.08 | 3718.26 | 3812.80 | 44.2 | 109.4 | 3750.54 | 3776.84 |
| h100_30_2_4 | 3783.46 | 3932.99 | 36.8 | 113.65 | 3874.50 | 3957.14 | 39.8 | 134.8 | 4029.02 | 4069.10 |
| h100_40_0_0 | 3872.08 | 4025.22 | 25.2 | 107.7 | 4037.28 | 4102.71 | 25.8 | 119.2 | 4065.76 | 4100.28 |
| h100_40_0_1 | 3937.38 | 4028.89 | 25.8 | 110.5 | 3924.94 | 4005.34 | 27.4 | 91 | 4082.98 | 4129.19 |
| h100_40_0_2 | 4027.06 | 4096.79 | 22.6 | 88.54 | 4038.82 | 4072.06 | 26.2 | 101.8 | 4070.90 | 4106.11 |
| h100_40_0_3 | 3882.64 | 3923.13 | 31.2 | 110.08 | 3861.82 | 3921.81 | 31.8 | 136.6 | 3919.56 | 3974.66 |
| h100_40_0_4 | 4122.08 | 4186.27 | 23.6 | 123.97 | 4042.88 | 4084.27 | 29 | 102.2 | 4143.36 | 4195.98 |
| h100_40_1_0 | 4447.40 | 4514.60 | 33.2 | 101.58 | 4349.46 | 4476.23 | 29.4 | 123.8 | 4503.38 | 4528.63 |
| h100_40_1_1 | 4386.10 | 4452.66 | 33.8 | 116.57 | 4380.64 | 4446.90 | 34.8 | 125 | 4439.68 | 4481.56 |
| h100_40_1_2 | 4396.34 | 4436.01 | 33 | 129.34 | 4396.52 | 4465.57 | 34.4 | 111.6 | 4437.78 | 4496.21 |
| h100_40_1_3 | 4295.88 | 4335.04 | 35.8 | 118.47 | 4275.06 | 4382.08 | 32.8 | 131.8 | 4339.76 | 4388.51 |
| h100_40_1_4 | 4479.10 | 4568.86 | 29.8 | 98.98 | 4544.14 | 4590.90 | 32.4 | 94.4 | 4527.80 | 4586.44 |
| h100_40_2_0 | 4545.96 | 4634.15 | 29.2 | 104.15 | 4603.64 | 4638.65 | 34.4 | 129.8 | 4608.80 | 4652.39 |
| h100_40_2_1 | 4480.66 | 4623.75 | 32 | 108.06 | 4491.28 | 4609.90 | 34.4 | 122.2 | 4561.18 | 4622.66 |
| h100_40_2_2 | 4612.04 | 4645.64 | 32 | 128.22 | 4601.72 | 4636.37 | 31.4 | 116.8 | 4576.02 | 4623.93 |
| h100_40_2_3 | 4369.82 | 4432.90 | 38.6 | 183.18 | 4377.48 | 4461.34 | 38 | 125.4 | 4439.96 | 4481.94 |
| h100_40_2_4 | 4668.38 | 4742.96 | 32.4 | 108.38 | 4712.68 | 4746.25 | 29.2 | 119.6 | 4640.92 | 4728.26 |

# APPENDIX D – The solutions obtained by the UBA and their comparisons with the ALNS-VS solutions

As mentioned in the manuscript, ALNS-VS_Unique solutions in Tables C1.-C.4 are adopted for further analysis. The column "UB" presents the objective function values of the solutions obtained by the proposed UBA. The "VS-UBA(%)" column indicates how much improvement on objective is offered by ALNS-VS over the UBA.

**Table D. 9.** UBA solutions and their comparisons with ALNS-VS solutions.

| Instance | UB | CPU | VS-UBA(%) | Instance | UB | CPU | VS-UBA(%) |
|---|---|---|---|---|---|---|---|
| h30_10_0_0 | 911.7 | 0.57 | 39.8 | h30_30_0_0 | 1426.2 | 0.22 | 32.7 |
| h30_10_0_1 | 892.2 | 0.15 | 35.9 | h30_30_0_1 | 1288.4 | 0.13 | 19.4 |
| h30_10_0_2 | 901.4 | 0.21 | 38.7 | h30_30_0_2 | 1299.6 | 0.13 | 18.9 |
| h30_10_0_3 | 907.7 | 0.26 | 37.1 | h30_30_0_3 | 1322.4 | 0.32 | 25.2 |
| h30_10_0_4 | 884.7 | 0.07 | 36.8 | h30_30_0_4 | 1246.7 | 0.16 | 22.4 |
| h30_10_1_0 | 1011.3 | 0.22 | 40.3 | h30_30_1_0 | 1409.2 | 0.14 | 25.8 |
| h30_10_1_1 | 979.3 | 0.16 | 37.3 | h30_30_1_1 | 1426.2 | 0.07 | 22.4 |
| h30_10_1_2 | 983.4 | 0.15 | 38.5 | h30_30_1_2 | 1381.6 | 0.1 | 24.2 |
| h30_10_1_3 | 984.1 | 0.32 | 39.3 | h30_30_1_3 | 1388.5 | 0.36 | 28.2 |
| h30_10_1_4 | 966.7 | 0.07 | 38.1 | h30_30_1_4 | 1336.2 | 0.06 | 24.5 |
| h30_10_2_0 | 1100.9 | 0.1 | 39.6 | h30_30_2_0 | 1561 | 0.11 | 31.5 |
| h30_10_2_1 | 1118.2 | 0.22 | 40.5 | h30_30_2_1 | 1514.4 | 0.11 | 23.2 |
| h30_10_2_2 | 1127.4 | 0.14 | 40.4 | h30_30_2_2 | 1472.1 | 0.14 | 22.3 |
| h30_10_2_3 | 1128.1 | 0.3 | 42.1 | h30_30_2_3 | 1532.5 | 0.38 | 31 |
| h30_10_2_4 | 1110.7 | 0.06 | 39.4 | h30_30_2_4 | 1472.7 | 0.09 | 27 |
| h30_20_0_0 | 1117.1 | 0.1 | 31.1 | h30_40_0_0 | 1545.5 | 0.32 | 24.7 |
| h30_20_0_1 | 1092.5 | 0.2 | 27.2 | h30_40_0_1 | 1487.8 | 0.16 | 16 |
| h30_20_0_2 | 1113.9 | 0.24 | 26.5 | h30_40_0_2 | 1505.3 | 0.13 | 15.3 |
| h30_20_0_3 | 1135.7 | 0.18 | 32.4 | h30_40_0_3 | 1521 | 0.18 | 22.4 |
| h30_20_0_4 | 1074.2 | 0.08 | 27.6 | h30_40_0_4 | 1437.6 | 0.15 | 17.2 |
| h30_20_1_0 | 1197.9 | 0.48 | 31.8 | h30_40_1_0 | 1703.2 | 0.22 | 26.4 |
| h30_20_1_1 | 1212.2 | 0.1 | 28.5 | h30_40_1_1 | 1585 | 0.07 | 16.2 |
| h30_20_1_2 | 1194.9 | 0.18 | 32.4 | h30_40_1_2 | 1597.5 | 0.22 | 20.3 |
| h30_20_1_3 | 1205.3 | 0.83 | 34.8 | h30_40_1_3 | 1586.5 | 0.26 | 22.8 |
| h30_20_1_4 | 1161.3 | 0.13 | 30.4 | h30_40_1_4 | 1530.5 | 0.08 | 20.5 |
| h30_20_2_0 | 1343.1 | 0.15 | 34.9 | h30_40_2_0 | 1736.5 | 0.09 | 25.2 |
| h30_20_2_1 | 1318.5 | 0.31 | 30 | h30_40_2_1 | 1713.8 | 0.1 | 17.5 |
| h30_20_2_2 | 1339.9 | 0.26 | 33.2 | h30_40_2_2 | 1658.1 | 0.14 | 18.7 |
| h30_20_2_3 | 1361.2 | 1.77 | 37.6 | h30_40_2_3 | 2650.4 | 0.28 | 50.7 |
| h30_20_2_4 | 1300.2 | 0.07 | 32 | h30_40_2_4 | 1663.6 | 0.06 | 25 |

| Instance | UB | CPU | VS-UBA(%) | Instance | UB | CPU | VS-UBA(%) |
|---|---|---|---|---|---|---|---|
| h50_10_0_0 | 1434.6 | 0.7 | 36.6 | h50_30_0_0 | 2093.8 | 0.52 | 25.1 |
| h50_10_0_1 | 1456.1 | 0.3 | 36.1 | h50_30_0_1 | 2161.8 | 0.25 | 26 |
| h50_10_0_2 | 1460.3 | 0.43 | 35.5 | h50_30_0_2 | 2177.6 | 0.22 | 22.9 |
| h50_10_0_3 | 1442.8 | 0.45 | 38.4 | h50_30_0_3 | 1886.8 | 2.34 | 20.3 |
| h50_10_0_4 | 1402.6 | 0.31 | 34.9 | h50_30_0_4 | 2174.7 | 0.18 | 25.5 |
| h50_10_1_0 | 1714.7 | 0.51 | 37.6 | h50_30_1_0 | 3315.6 | 0.54 | 48 |
| h50_10_1_1 | 1702.2 | 0.18 | 37 | h50_30_1_1 | 2364.6 | 0.19 | 26.2 |
| h50_10_1_2 | 1719.6 | 0.24 | 38.7 | h50_30_1_2 | 2490.6 | 0.25 | 27.4 |
| h50_10_1_3 | 1716.8 | 0.41 | 40.5 | h50_30_1_3 | 2160.8 | 2.37 | 24.8 |
| h50_10_1_4 | 1676.5 | 0.32 | 38.6 | h50_30_1_4 | 2398.7 | 0.66 | 27.3 |
| h50_10_2_0 | 2018.7 | 0.51 | 40 | h50_30_2_0 | 3566.2 | 0.52 | 48.5 |
| h50_10_2_1 | 2032.5 | 0.31 | 40 | h50_30_2_1 | 2732.7 | 0.32 | 29.1 |
| h50_10_2_2 | 2038.3 | 0.5 | 40.3 | h50_30_2_2 | 2731.3 | 0.29 | 27.5 |
| h50_10_2_3 | 2020.8 | 0.38 | 41.5 | h50_30_2_3 | 2464.8 | 2.91 | 28.4 |
| h50_10_2_4 | 1974.7 | 0.29 | 38.8 | h50_30_2_4 | 2584.1 | 0.54 | 25.3 |
| h50_20_0_0 | 1789.9 | 0.46 | 29.2 | h50_40_0_0 | 2424.6 | 0.92 | 22.8 |
| h50_20_0_1 | 1787.1 | 0.23 | 27.3 | h50_40_0_1 | 2602.5 | 0.34 | 24.2 |
| h50_20_0_2 | 1766.2 | 0.27 | 26.3 | h50_40_0_2 | 2427 | 0.19 | 17.1 |
| h50_20_0_3 | 1680 | 0.61 | 30 | h50_40_0_3 | 2149.1 | 1.72 | 17.4 |
| h50_20_0_4 | 1818.4 | 0.23 | 29.6 | h50_40_0_4 | 3492.6 | 0.65 | 44.1 |
| h50_20_1_0 | 2042.2 | 0.4 | 31.1 | h50_40_1_0 | 5516.2 | 0.48 | 62.9 |
| h50_20_1_1 | 2043 | 0.17 | 32.3 | h50_40_1_1 | 3776.5 | 0.48 | 45.2 |
| h50_20_1_2 | 2077.9 | 0.24 | 29.5 | h50_40_1_2 | 4709 | 0.24 | 54.5 |
| h50_20_1_3 | 1889.1 | 0.51 | 29.5 | h50_40_1_3 | 2423.1 | 2.1 | 21 |
| h50_20_1_4 | 2061.2 | 0.56 | 32.9 | h50_40_1_4 | 2607.6 | 0.83 | 20.2 |
| h50_20_2_0 | 2346.2 | 0.42 | 32.2 | h50_40_2_0 | 5791.2 | 0.53 | 60.5 |
| h50_20_2_1 | 2365.1 | 0.19 | 32.8 | h50_40_2_1 | 8733.6 | 0.28 | 73.7 |
| h50_20_2_2 | 2344.2 | 0.25 | 31.6 | h50_40_2_2 | 6680.1 | 0.28 | 64.8 |
| h50_20_2_3 | 2290.8 | 0.5 | 36 | h50_40_2_3 | 2841.8 | 0.59 | 27.6 |
| h50_20_2_4 | 2293.8 | 0.65 | 32.7 | h50_40_2_4 | 3849 | 0.39 | 40.5 |
| h100_10_0_0 | 3004.5 | 1.61 | 34.2 | h100_30_0_0 | 4307.1 | 2.82 | 24 |
| h100_10_0_1 | 2979.1 | 1.07 | 31.1 | h100_30_0_1 | 4221.4 | 0.55 | 19.5 |
| h100_10_0_2 | 2999.6 | 0.66 | 31.9 | h100_30_0_2 | 4213.4 | 1.14 | 23.1 |
| h100_10_0_3 | 2998.3 | 0.98 | 32.8 | h100_30_0_3 | 4275.9 | 0.67 | 25.4 |
| h100_10_0_4 | 3032.2 | 1.15 | 35.1 | h100_30_0_4 | 4402.6 | 0.56 | 22.8 |
| h100_10_1_0 | 3686 | 0.97 | 35.4 | h100_30_1_0 | 4931.5 | 0.88 | 24.9 |
| h100_10_1_1 | 3685 | 0.75 | 36.9 | h100_30_1_1 | 5076.5 | 0.54 | 26.8 |
| h100_10_1_2 | 3704.7 | 0.78 | 35.5 | h100_30_1_2 | 5018.3 | 0.74 | 27.3 |
| h100_10_1_3 | 3683.6 | 1.07 | 36.8 | h100_30_1_3 | 4855.2 | 2.2 | 26.1 |
| h100_10_1_4 | 3696.6 | 1.25 | 35.7 | h100_30_1_4 | 4982.6 | 0.52 | 25 |
| h100_10_2_0 | 3863.7 | 1.52 | 35.5 | h100_30_2_0 | 5050.6 | 2.7 | 23.3 |
| h100_10_2_1 | 3834.7 | 0.97 | 37.1 | h100_30_2_1 | 5111 | 0.58 | 25.1 |

| Instance | UB | CPU | VS-UBA(%) | Instance | UB | CPU | VS-UBA(%) |
|---|---|---|---|---|---|---|---|
| h100_10_2_2 | 3848 | 1.45 | 35.5 | h100_30_2_2 | 5199.9 | 1.41 | 29 |
| h100_10_2_3 | 3845.6 | 1.7 | 36.1 | h100_30_2_3 | 5148.3 | 0.85 | 27.4 |
| h100_10_2_4 | 3859.2 | 2.4 | 35.8 | h100_30_2_4 | 5171.9 | 0.57 | 26.8 |
| h100_20_0_0 | 3553 | 2.64 | 25.2 | h100_40_0_0 | 4964.7 | 3.76 | 22 |
| h100_20_0_1 | 3706.7 | 1.29 | 27.6 | h100_40_0_1 | 4851.8 | 0.6 | 18.8 |
| h100_20_0_2 | 3710.5 | 1.88 | 29.6 | h100_40_0_2 | 4917 | 1.14 | 18.1 |
| h100_20_0_3 | 3668.2 | 1.61 | 28.3 | h100_40_0_3 | 4911.8 | 0.49 | 21 |
| h100_20_0_4 | 3666.2 | 0.95 | 25.9 | h100_40_0_4 | 5091.4 | 0.54 | 19 |
| h100_20_1_0 | 4274.2 | 2.05 | 29.2 | h100_40_1_0 | 7646.1 | 0.88 | 41.8 |
| h100_20_1_1 | 4415.4 | 1.2 | 32 | h100_40_1_1 | 9488.7 | 1.82 | 53.8 |
| h100_20_1_2 | 4425 | 3.63 | 31.4 | h100_40_1_2 | 10561.2 | 0.79 | 58.4 |
| h100_20_1_3 | 4270.6 | 1.37 | 27.9 | h100_40_1_3 | 12520.1 | 1.17 | 65.7 |
| h100_20_1_4 | 4356.7 | 0.78 | 29.1 | h100_40_1_4 | 11516.5 | 0.92 | 61.1 |
| h100_20_2_0 | 4430.4 | 1.86 | 28.3 | h100_40_2_0 | 11453.7 | 2.92 | 60.3 |
| h100_20_2_1 | 4501 | 1.27 | 30.4 | h100_40_2_1 | 12504.8 | 1.13 | 64.2 |
| h100_20_2_2 | 4613.5 | 2.5 | 32 | h100_40_2_2 | 9613.9 | 4.91 | 52 |
| h100_20_2_3 | 4443.8 | 2.16 | 30.6 | h100_40_2_3 | 9537.6 | 1.79 | 54.2 |
| h100_20_2_4 | 4523.2 | 1.55 | 29.8 | h100_40_2_4 | 10626.1 | 0.91 | 56.1 |

## APPENDIX E – The effect of DP policy and the HHSRP-M solutions

In Chapter 5.5, we discussed the effect of DP policy on total flow time by comparing the solutions of the HHSRP-M with the HHSRP-VS. In this appendix, Tables E.1 through E.4 demonstrates the solutions obtained by the ALNS-M and their comparisons with the ALNS-VS in details. As mentioned in the manuscript, ALNS-VS_Unique solutions in Tables D1.-D.4 are adopted for further analysis. In the following tables, the "Best-found" and "Avg." columns indicate the objective values of the best-found and the averages of the best solutions found in five replications by the ALNS-M, respectively. Additionally, the column "VS-M%" presents the percentage improvement on the objective offered by ALNS-VS over the ALNS-M.

**Table E. 10.** ALNS-M solutions for 10-patient instances and their comparisons with ALNS-VS.

| Instance | Best-found | Avg. | CPU | VS-M(%) | Instance | Best-found | Avg. | CPU | VS-M(%) |
|---|---|---|---|---|---|---|---|---|---|
| h10_10_0_0 | 318.6 | 318.6 | 1.09 | 24.5 | h10_30_0_0 | 506.5 | 506.5 | 1.05 | 6.7 |
| h10_10_0_1 | 338.7 | 338.7 | 1.04 | 24.9 | h10_30_0_1 | 569.1 | 569.1 | 1.07 | 7.3 |
| h10_10_0_2 | 333.2 | 333.2 | 1.06 | 30.3 | h10_30_0_2 | 552.3 | 552.3 | 1.04 | 9.4 |
| h10_10_0_3 | 337.2 | 337.2 | 1.07 | 24.2 | h10_30_0_3 | 558.5 | 558.5 | 1.06 | 9.7 |
| h10_10_0_4 | 318.2 | 318.2 | 1.02 | 31.7 | h10_30_0_4 | 514.1 | 514.1 | 1.00 | 12.5 |
| h10_10_1_0 | 362.6 | 362.6 | 1.04 | 29.3 | h10_30_1_0 | 550.5 | 550.5 | 1.11 | 5.6 |
| h10_10_1_1 | 382.7 | 382.7 | 1.03 | 26.3 | h10_30_1_1 | 613.1 | 613.1 | 1.02 | 11.2 |
| h10_10_1_2 | 377.2 | 377.2 | 1.02 | 35.6 | h10_30_1_2 | 596.3 | 596.3 | 1.06 | 7.0 |
| h10_10_1_3 | 381.2 | 381.2 | 1.02 | 28.7 | h10_30_1_3 | 602.5 | 602.5 | 1.06 | 12.4 |
| h10_10_1_4 | 362.2 | 362.2 | 0.96 | 34.4 | h10_30_1_4 | 558.1 | 558.1 | 0.97 | 13.2 |
| h10_10_2_0 | 424.6 | 424.6 | 1.02 | 34.5 | h10_30_2_0 | 612.5 | 612.5 | 1.05 | 12.1 |
| h10_10_2_1 | 444.7 | 444.7 | 1.02 | 30.7 | h10_30_2_1 | 675.1 | 675.1 | 1.09 | 10.0 |
| h10_10_2_2 | 439.2 | 439.2 | 1.02 | 37.0 | h10_30_2_2 | 658.3 | 658.3 | 1.07 | 12.3 |
| h10_10_2_3 | 443.2 | 443.2 | 1.02 | 30.9 | h10_30_2_3 | 664.5 | 664.5 | 1.06 | 17.4 |
| h10_10_2_4 | 424.2 | 424.2 | 0.98 | 34.2 | h10_30_2_4 | 620.1 | 620.1 | 0.98 | 20.0 |
| h10_20_0_0 | 415.4 | 415.4 | 1.06 | 10.5 | h10_40_0_0 | 602.7 | 602.7 | 1.06 | 5.9 |
| h10_20_0_1 | 449.0 | 449.0 | 1.04 | 10.7 | h10_40_0_1 | 687.4 | 687.4 | 1.05 | 6.2 |
| h10_20_0_2 | 442.8 | 442.8 | 1.04 | 16.6 | h10_40_0_2 | 659.9 | 659.9 | 1.04 | 6.9 |
| h10_20_0_3 | 444.7 | 444.7 | 1.57 | 13.5 | h10_40_0_3 | 669.5 | 669.5 | 1.03 | 7.5 |
| h10_20_0_4 | 418.6 | 418.6 | 1.01 | 18.9 | h10_40_0_4 | 608.6 | 608.6 | 1.12 | 9.3 |
| h10_20_1_0 | 459.4 | 459.4 | 1.06 | 17.5 | h10_40_1_0 | 646.7 | 646.7 | 2.85 | 4.9 |
| h10_20_1_1 | 493.0 | 493.0 | 1.06 | 16.2 | h10_40_1_1 | 731.4 | 731.4 | 1.51 | 9.0 |
| h10_20_1_2 | 486.8 | 486.8 | 1.05 | 19.6 | h10_40_1_2 | 703.9 | 703.9 | 1.00 | 3.7 |
| h10_20_1_3 | 488.7 | 488.7 | 1.10 | 18.6 | h10_40_1_3 | 713.5 | 713.5 | 1.00 | 8.9 |
| h10_20_1_4 | 462.6 | 462.6 | 0.97 | 22.9 | h10_40_1_4 | 652.6 | 652.6 | 0.93 | 8.0 |
| h10_20_2_0 | 521.4 | 521.4 | 1.04 | 15.6 | h10_40_2_0 | 708.7 | 708.7 | 1.01 | 9.7 |
| h10_20_2_1 | 555.0 | 555.0 | 1.04 | 15.9 | h10_40_2_1 | 793.4 | 793.4 | 0.99 | 6.3 |
| h10_20_2_2 | 548.8 | 548.8 | 1.08 | 20.4 | h10_40_2_2 | 765.9 | 765.9 | 0.99 | 8.0 |
| h10_20_2_3 | 550.7 | 550.7 | 1.06 | 21.2 | h10_40_2_3 | 775.5 | 775.5 | 1.00 | 14.1 |
| h10_20_2_4 | 524.6 | 524.6 | 0.97 | 27.4 | h10_40_2_4 | 714.6 | 714.6 | 1.03 | 15.9 |

**Table E. 11.** ALNS-M solutions for 30-patient instances and their comparisons with ALNS-VS.

| Instance | Best-found | Avg. | CPU | VS-M(%) | Instance | Best-found | Avg. | CPU | VS-M(%) |
|---|---|---|---|---|---|---|---|---|---|
| h30_10_0_0 | 846.8 | 849.7 | 17.1 | 35.4 | h30_30_0_0 | 1182.9 | 1188.7 | 11.0 | 19.3 |
| h30_10_0_1 | 863.3 | 864.7 | 12.9 | 33.9 | h30_30_0_1 | 1226.4 | 1228.6 | 12.4 | 15.4 |
| h30_10_0_2 | 876.0 | 879.5 | 10.9 | 37.2 | h30_30_0_2 | 1230.5 | 1230.5 | 12.0 | 14.4 |
| h30_10_0_3 | 856.4 | 864.5 | 12.0 | 33.9 | h30_30_0_3 | 1203.3 | 1206.9 | 13.4 | 18.0 |
| h30_10_0_4 | 855.7 | 855.8 | 11.1 | 34.6 | h30_30_0_4 | 1171.6 | 1171.6 | 13.0 | 17.4 |
| h30_10_1_0 | 928.8 | 933.8 | 12.6 | 35.3 | h30_30_1_0 | 1272.2 | 1274.6 | 15.3 | 18.0 |
| h30_10_1_1 | 945.3 | 945.3 | 13.8 | 35.0 | h30_30_1_1 | 1312.0 | 1312.0 | 18.3 | 15.7 |
| h30_10_1_2 | 958.0 | 961.5 | 11.0 | 37.1 | h30_30_1_2 | 1312.5 | 1312.5 | 17.1 | 20.2 |
| h30_10_1_3 | 938.4 | 946.5 | 12.4 | 36.9 | h30_30_1_3 | 1285.3 | 1288.9 | 17.7 | 22.7 |
| h30_10_1_4 | 937.7 | 937.8 | 12.4 | 36.2 | h30_30_1_4 | 1253.6 | 1253.6 | 15.1 | 19.6 |
| h30_10_2_0 | 1082.8 | 1082.8 | 12.3 | 38.6 | h30_30_2_0 | 1422.2 | 1427.2 | 17.8 | 25.1 |
| h30_10_2_1 | 1098.3 | 1099.6 | 11.9 | 39.5 | h30_30_2_1 | 1458.2 | 1458.2 | 18.1 | 20.2 |
| h30_10_2_2 | 1106.3 | 1106.3 | 10.0 | 39.3 | h30_30_2_2 | 1467.5 | 1467.5 | 16.0 | 22.0 |
| h30_10_2_3 | 1089.6 | 1089.8 | 12.2 | 40.1 | h30_30_2_3 | 1429.3 | 1432.8 | 18.4 | 26.2 |
| h30_10_2_4 | 1081.9 | 1081.9 | 9.4 | 37.8 | h30_30_2_4 | 1397.6 | 1397.6 | 15.3 | 23.1 |
| h30_20_0_0 | 1019.0 | 1019.0 | 11.9 | 24.4 | h30_40_0_0 | 1350.8 | 1362.0 | 18.4 | 14.6 |
| h30_20_0_1 | 1047.8 | 1049.7 | 11.6 | 24.2 | h30_40_0_1 | 1413.7 | 1413.7 | 19.6 | 11.6 |
| h30_20_0_2 | 1045.1 | 1050.1 | 10.2 | 22.1 | h30_40_0_2 | 1426.5 | 1426.5 | 18.5 | 10.6 |
| h30_20_0_3 | 1017.1 | 1025.1 | 11.8 | 25.1 | h30_40_0_3 | 1369.7 | 1374.1 | 18.9 | 14.1 |
| h30_20_0_4 | 1025.2 | 1025.2 | 9.4 | 24.2 | h30_40_0_4 | 1340.6 | 1340.6 | 16.4 | 11.2 |
| h30_20_1_0 | 1112.9 | 1113.3 | 10.7 | 26.6 | h30_40_1_0 | 1432.8 | 1434.6 | 17.6 | 12.7 |
| h30_20_1_1 | 1131.6 | 1132.7 | 11.5 | 23.5 | h30_40_1_1 | 1498.7 | 1499.2 | 18.6 | 11.4 |
| h30_20_1_2 | 1133.4 | 1133.4 | 9.9 | 28.7 | h30_40_1_2 | 1508.5 | 1508.5 | 18.7 | 15.6 |
| h30_20_1_3 | 1110.0 | 1115.7 | 11.2 | 29.6 | h30_40_1_3 | 1471.6 | 1476.4 | 19.6 | 17.1 |
| h30_20_1_4 | 1107.2 | 1107.2 | 9.5 | 26.9 | h30_40_1_4 | 1422.6 | 1422.6 | 17.3 | 14.4 |
| h30_20_2_0 | 1256.9 | 1257.8 | 11.0 | 30.4 | h30_40_2_0 | 1579.7 | 1610.7 | 18.5 | 19.4 |
| h30_20_2_1 | 1280.7 | 1280.7 | 10.9 | 27.9 | h30_40_2_1 | 1654.0 | 1654.0 | 20.2 | 14.5 |
| h30_20_2_2 | 1282.3 | 1282.3 | 9.5 | 30.2 | h30_40_2_2 | 1657.8 | 1664.1 | 17.0 | 19.0 |
| h30_20_2_3 | 1258.4 | 1260.3 | 11.0 | 32.6 | h30_40_2_3 | 1611.7 | 1620.9 | 18.5 | 19.4 |
| h30_20_2_4 | 1251.2 | 1251.2 | 9.8 | 29.4 | h30_40_2_4 | 1566.6 | 1566.6 | 16.3 | 20.4 |

**Table E. 12.** ALNS-M solutions for 50-patient instances and their comparisons with ALNS-VS.

| Instance | Best-found | Avg. | CPU | VS-M(%) | Instance | Best-found | Avg. | CPU | VS-M(%) |
|---|---|---|---|---|---|---|---|---|---|
| h50_10_0_0 | 1371.0 | 1374.0 | 33 | 33.6 | h50_30_0_0 | 1883.9 | 1892.9 | 38 | 16.7 |
| h50_10_0_1 | 1367.1 | 1372.0 | 31 | 31.9 | h50_30_0_1 | 1901.0 | 1915.3 | 38 | 15.9 |
| h50_10_0_2 | 1367.9 | 1372.9 | 34 | 31.1 | h50_30_0_2 | 1898.0 | 1938.3 | 38 | 11.5 |
| h50_10_0_3 | 1339.5 | 1343.4 | 35 | 33.6 | h50_30_0_3 | 1806.0 | 1820.7 | 39 | 16.7 |
| h50_10_0_4 | 1366.2 | 1371.5 | 41 | 33.1 | h50_30_0_4 | 1886.3 | 1900.2 | 38 | 14.1 |
| h50_10_1_0 | 1642.4 | 1647.6 | 40 | 34.8 | h50_30_1_0 | 2171.1 | 2182.5 | 35 | 20.6 |
| h50_10_1_1 | 1641.1 | 1645.0 | 35 | 34.6 | h50_30_1_1 | 2160.6 | 2178.7 | 28 | 19.2 |

| Instance | Best-found | Avg. | CPU | VS-M(%) | Instance | Best-found | Avg. | CPU | VS-M(%) |
|---|---|---|---|---|---|---|---|---|---|
| h50_10_1_2 | 1638.5 | 1644.8 | 42 | 35.7 | h50_30_1_2 | 2190.9 | 2201.9 | 20 | 17.5 |
| h50_10_1_3 | 1612.2 | 1619.5 | 39 | 36.7 | h50_30_1_3 | 2088.2 | 2097.1 | 20 | 22.1 |
| h50_10_1_4 | 1636.8 | 1643.2 | 42 | 37.1 | h50_30_1_4 | 2161.5 | 2183.0 | 20 | 19.3 |
| h50_10_2_0 | 1950.0 | 1952.8 | 41 | 37.9 | h50_30_2_0 | 2464.0 | 2498.7 | 20 | 25.5 |
| h50_10_2_1 | 1948.7 | 1951.2 | 37 | 37.4 | h50_30_2_1 | 2488.0 | 2498.8 | 20 | 22.1 |
| h50_10_2_2 | 1953.4 | 1955.6 | 40 | 37.7 | h50_30_2_2 | 2504.9 | 2523.6 | 20 | 21.0 |
| h50_10_2_3 | 1916.3 | 1918.6 | 41 | 38.3 | h50_30_2_3 | 2398.0 | 2403.9 | 20 | 26.4 |
| h50_10_2_4 | 1940.8 | 1950.9 | 35 | 37.8 | h50_30_2_4 | 2469.0 | 2495.5 | 20 | 21.8 |
| h50_20_0_0 | 1627.0 | 1628.9 | 44 | 22.1 | h50_40_0_0 | 2145.5 | 2182.5 | 20 | 12.8 |
| h50_20_0_1 | 1625.8 | 1636.9 | 36 | 20.1 | h50_40_0_1 | 2161.1 | 2191.3 | 20 | 8.8 |
| h50_20_0_2 | 1631.3 | 1638.1 | 42 | 20.2 | h50_40_0_2 | 2186.5 | 2207.8 | 20 | 8.0 |
| h50_20_0_3 | 1578.7 | 1580.7 | 24 | 25.5 | h50_40_0_3 | 2056.0 | 2063.1 | 20 | 13.7 |
| h50_20_0_4 | 1624.2 | 1627.6 | 27 | 21.1 | h50_40_0_4 | 2145.7 | 2153.8 | 20 | 9.1 |
| h50_20_1_0 | 1901.0 | 1909.5 | 26 | 26.0 | h50_40_1_0 | 2420.2 | 2471.9 | 20 | 15.4 |
| h50_20_1_1 | 1899.8 | 1912.6 | 25 | 27.2 | h50_40_1_1 | 2435.1 | 2463.1 | 20 | 14.9 |
| h50_20_1_2 | 1909.0 | 1922.2 | 33 | 23.2 | h50_40_1_2 | 2467.4 | 2485.9 | 20 | 13.1 |
| h50_20_1_3 | 1844.8 | 1851.4 | 43 | 27.8 | h50_40_1_3 | 2330.3 | 2343.8 | 20 | 17.9 |
| h50_20_1_4 | 1900.0 | 1903.6 | 45 | 27.2 | h50_40_1_4 | 2427.7 | 2461.9 | 20 | 14.3 |
| h50_20_2_0 | 2207.8 | 2211.4 | 42 | 27.9 | h50_40_2_0 | 2744.9 | 2806.3 | 20 | 16.7 |
| h50_20_2_1 | 2203.8 | 2216.8 | 38 | 27.9 | h50_40_2_1 | 2754.6 | 2799.3 | 20 | 16.8 |
| h50_20_2_2 | 2212.1 | 2219.1 | 39 | 27.5 | h50_40_2_2 | 2809.8 | 3002.9 | 20 | 16.3 |
| h50_20_2_3 | 2152.3 | 2156.7 | 35 | 31.9 | h50_40_2_3 | 2662.0 | 2662.0 | 20 | 22.7 |
| h50_20_2_4 | 2205.8 | 2220.2 | 36 | 30.0 | h50_40_2_4 | 2738.8 | 2774.0 | 20 | 16.4 |

**Table E.13.** ALNS-M solutions for 100-patient instances and their comparisons with ALNS-VS.

| Instance | Best-found | Avg. | CPU | VS-M(%) | Instance | Best-found | Avg. | CPU | VS-M(%) |
|---|---|---|---|---|---|---|---|---|---|
| h100_10_0_0 | 2867.7 | 2891.2 | 63 | 31.1 | h100_30_0_0 | 3927.5 | 3965.8 | 62 | 16.7 |
| h100_10_0_1 | 2861.3 | 2868.6 | 65 | 28.3 | h100_30_0_1 | 3883.6 | 3912.8 | 62 | 12.5 |
| h100_10_0_2 | 2876.0 | 2886.5 | 65 | 29.0 | h100_30_0_2 | 3930.7 | 3950.4 | 64 | 17.5 |
| h100_10_0_3 | 2859.4 | 2884.4 | 64 | 29.6 | h100_30_0_3 | 3864.3 | 3893.5 | 64 | 17.4 |
| h100_10_0_4 | 2889.1 | 2900.7 | 63 | 31.9 | h100_30_0_4 | 3939.7 | 3966.2 | 63 | 13.7 |
| h100_10_1_0 | 3564.8 | 3571.7 | 67 | 33.2 | h100_30_1_0 | 4610.1 | 4645.9 | 60 | 19.7 |
| h100_10_1_1 | 3544.1 | 3551.1 | 65 | 34.3 | h100_30_1_1 | 4610.6 | 4620.2 | 60 | 19.5 |
| h100_10_1_2 | 3545.8 | 3559.2 | 65 | 32.6 | h100_30_1_2 | 4599.5 | 4627.1 | 61 | 20.7 |
| h100_10_1_3 | 3546.0 | 3561.1 | 66 | 34.4 | h100_30_1_3 | 4557.4 | 4580.9 | 60 | 21.3 |
| h100_10_1_4 | 3565.1 | 3578.5 | 65 | 33.3 | h100_30_1_4 | 4647.2 | 4671.9 | 60 | 19.6 |
| h100_10_2_0 | 3724.1 | 3738.9 | 65 | 33.1 | h100_30_2_0 | 4762.8 | 4814.4 | 60 | 18.6 |
| h100_10_2_1 | 3707.7 | 3712.7 | 65 | 34.9 | h100_30_2_1 | 4770.2 | 4770.2 | 60 | 19.7 |
| h100_10_2_2 | 3715.7 | 3723.4 | 65 | 33.2 | h100_30_2_2 | 4800.1 | 4810.5 | 60 | 23.1 |
| h100_10_2_3 | 3711.8 | 3718.9 | 65 | 33.8 | h100_30_2_3 | 4715.6 | 4731.1 | 60 | 20.8 |
| h100_10_2_4 | 3736.7 | 3748.2 | 66 | 33.7 | h100_30_2_4 | 4869.2 | 4885.9 | 63 | 22.3 |

| Instance | Best-found | Avg. | CPU | VS-M (%) | Instance | Best-found | Avg. | CPU | VS-M (%) |
|---|---|---|---|---|---|---|---|---|---|
| h100_20_0_0 | 3412.3 | 3412.3 | 63 | 22.1 | h100_40_0_0 | 4409.2 | 4475.7 | 61 | 12.2 |
| h100_20_0_1 | 3372.6 | 3400.2 | 65 | 20.5 | h100_40_0_1 | 4394.0 | 4491.5 | 62 | 10.4 |
| h100_20_0_2 | 3396.5 | 3402.0 | 65 | 23.1 | h100_40_0_2 | 4468.0 | 4497.0 | 63 | 9.9 |
| h100_20_0_3 | 3349.3 | 3379.4 | 64 | 21.5 | h100_40_0_3 | 4404.9 | 4427.3 | 62 | 11.9 |
| h100_20_0_4 | 3415.4 | 3458.0 | 64 | 20.4 | h100_40_0_4 | 4473.4 | 4540.0 | 60 | 7.9 |
| h100_20_1_0 | 4077.7 | 4091.4 | 61 | 25.8 | h100_40_1_0 | 5220.2 | 5225.9 | 61 | 14.8 |
| h100_20_1_1 | 4089.2 | 4101.6 | 63 | 26.5 | h100_40_1_1 | 5149.0 | 5205.4 | 62 | 14.8 |
| h100_20_1_2 | 4073.7 | 4076.1 | 66 | 25.5 | h100_40_1_2 | 5182.6 | 5186.0 | 63 | 15.2 |
| h100_20_1_3 | 4059.2 | 4066.6 | 67 | 24.2 | h100_40_1_3 | 5145.1 | 5186.9 | 60 | 16.5 |
| h100_20_1_4 | 4111.1 | 4133.8 | 65 | 24.8 | h100_40_1_4 | 5266.3 | 5280.1 | 64 | 14.9 |
| h100_20_2_0 | 4215.0 | 4255.3 | 62 | 24.6 | h100_40_2_0 | 5365.4 | 5409.0 | 67 | 15.3 |
| h100_20_2_1 | 4221.5 | 4240.4 | 66 | 25.8 | h100_40_2_1 | 5390.7 | 5435.7 | 62 | 16.9 |
| h100_20_2_2 | 4234.5 | 4242.4 | 66 | 25.9 | h100_40_2_2 | 5324.2 | 5344.4 | 63 | 13.4 |
| h100_20_2_3 | 4229.5 | 4231.1 | 64 | 27.1 | h100_40_2_3 | 5311.0 | 5323.8 | 61 | 17.7 |
| h100_20_2_4 | 4252.2 | 4290.1 | 67 | 25.4 | h100_40_2_4 | 5293.3 | 5404.9 | 64 | 11.8 |

**Table E. 14.** ANOVA table for analyzing the contribution of DP.

| *Source* | *DF* | *Adj SS* | *Adj MS* | *F-Value* | *p-Value* |
|---|---|---|---|---|---|
| $\boldsymbol{noP}$ | 3 | 2171.55 | 723.85 | 138.08 | 0.000 |
| $\boldsymbol{ra}$ | 3 | 14833.40 | 4944.47 | 943.17 | 0.000 |
| $\boldsymbol{dd}$ | 2 | 1269.85 | 634.92 | 121.11 | 0.000 |
| $\boldsymbol{noP} * \boldsymbol{ra}$ | 9 | 164.41 | 18.27 | 3.48 | 0.001 |
| $\boldsymbol{noP} * \boldsymbol{dd}$ | 6 | 94.16 | 15.69 | 2.99 | 0.008 |
| $\boldsymbol{ra} * \boldsymbol{dd}$ | 6 | 24.24 | 4.04 | 0.77 | 0.594 |
| $\boldsymbol{no} * \boldsymbol{ra} * \boldsymbol{dd}$ | 18 | 54.51 | 3.03 | 0.58 | 0.913 |
| *Error* | 192 | 1006.54 | 5.24 | | |
| *Total* | 239 | 19618.65 | | | |

## APPENDIX F – The effect of vehicle sharing with DP policy and the HHSRP-STD solutions

In Chapter 5.5, we discussed the effect of the vehicle sharing with DP policy on total flow time by comparing the solutions of the HHSRP-STD with the HHSRP-VS. In this appendix, Tables F.1 through F.4 demonstrates the solutions obtained by the ALNS-STD. In the following tables, the “Best-found” and “Avg.” columns indicate the objective values of the best-found and the averages of the best solutions found in five replications by the ALNS-STD, respectively. The column “ALNS-VS” shows the best-found solution by the ALNS-VS. The column “ADD” presents the increase in total working time of the caregivers caused by the vehicle sharing with DP policy, which is simple the different between the best-found solutions of ALNS-STD and ALNS-VS. Moreover, the column “$BER$" demonstrates the break-even ratios.

**Table F. 15.** ALNS-STD solutions and break-even ratios for 10-patient instances.

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h10_10_0_0 | 174.62 | 174.62 | 240.54 | 65.92 | 1.2 |
| h10_10_0_1 | 178.48 | 178.48 | 254.28 | 75.8 | 1.5 |
| h10_10_0_2 | 177.72 | 177.72 | 232.1 | 54.38 | 0.9 |
| h10_10_0_3 | 176.36 | 176.36 | 255.76 | 79.4 | 1.6 |
| h10_10_0_4 | 176.15 | 177.454 | 217.24 | 41.09 | 0.6 |
| h10_10_1_0 | 195.87 | 196.798 | 256.26 | 60.39 | 0.9 |
| h10_10_1_1 | 200.48 | 200.48 | 281.98 | 81.5 | 1.4 |
| h10_10_1_2 | 199.72 | 199.72 | 243.04 | 43.32 | 0.6 |
| h10_10_1_3 | 198.36 | 198.36 | 271.96 | 73.6 | 1.2 |
| h10_10_1_4 | 198.15 | 198.15 | 237.54 | 39.39 | 0.5 |
| h10_10_2_0 | 226.87 | 227.17 | 278.02 | 51.15 | 0.6 |
| h10_10_2_1 | 231.48 | 231.48 | 308.08 | 76.6 | 1 |
| h10_10_2_2 | 230.72 | 230.72 | 276.56 | 45.84 | 0.5 |
| h10_10_2_3 | 229.36 | 229.36 | 306.36 | 77 | 1 |
| h10_10_2_4 | 229.15 | 230.454 | 279.24 | 50.09 | 0.6 |
| h10_20_0_0 | 236 | 237.986 | 371.66 | 135.66 | 2.7 |
| h10_20_0_1 | 243.81 | 243.81 | 401.04 | 157.23 | 3.6 |
| h10_20_0_2 | 242.07 | 242.07 | 369.14 | 127.07 | 2.2 |
| h10_20_0_3 | 236.34 | 236.34 | 384.52 | 148.18 | 3.4 |
| h10_20_0_4 | 240.78 | 242.842 | 339.46 | 98.68 | 1.4 |
| h10_20_1_0 | 258 | 259.344 | 379.22 | 121.22 | 1.8 |
| h10_20_1_1 | 265.81 | 265.81 | 413.12 | 147.31 | 2.5 |
| h10_20_1_2 | 264.07 | 264.07 | 391.6 | 127.53 | 1.9 |

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h10_20_1_3 | 258.34 | 258.34 | 397.7 | 139.36 | 2.3 |
| h10_20_1_4 | 262.78 | 266.904 | 356.78 | 94 | 1.1 |
| h10_20_2_0 | 290.68 | 291.322 | 440.16 | 149.48 | 2.1 |
| h10_20_2_1 | 296.81 | 296.81 | 466.62 | 169.81 | 2.7 |
| h10_20_2_2 | 295.07 | 295.07 | 437.02 | 141.95 | 1.9 |
| h10_20_2_3 | 289.34 | 289.34 | 433.98 | 144.64 | 2 |
| h10_20_2_4 | 293.78 | 298.466 | 380.64 | 86.86 | 0.8 |
| h10_30_0_0 | 296.95 | 299.102 | 472.46 | 175.51 | 2.9 |
| h10_30_0_1 | 311.45 | 311.45 | 527.26 | 215.81 | 4.5 |
| h10_30_0_2 | 307.78 | 308.232 | 500.28 | 192.5 | 3.3 |
| h10_30_0_3 | 301.45 | 301.45 | 504.56 | 203.11 | 4.1 |
| h10_30_0_4 | 306.31 | 314.118 | 449.6 | 143.29 | 1.8 |
| h10_30_1_0 | 318.95 | 321.102 | 519.86 | 200.91 | 3.4 |
| h10_30_1_1 | 333.45 | 333.45 | 544.58 | 211.13 | 3.5 |
| h10_30_1_2 | 329.78 | 330.684 | 554.74 | 224.96 | 4.3 |
| h10_30_1_3 | 323.45 | 323.45 | 527.82 | 204.37 | 3.4 |
| h10_30_1_4 | 328.31 | 331.506 | 484.16 | 155.85 | 1.8 |
| h10_30_2_0 | 349.95 | 352.102 | 538.44 | 188.49 | 2.3 |
| h10_30_2_1 | 364.45 | 364.45 | 607.64 | 243.19 | 4 |
| h10_30_2_2 | 360.78 | 360.78 | 577.62 | 216.84 | 3 |
| h10_30_2_3 | 354.45 | 354.45 | 548.68 | 194.23 | 2.4 |
| h10_30_2_4 | 359.31 | 367.118 | 496.08 | 136.77 | 1.2 |
| h10_40_0_0 | 358.74 | 360.948 | 567.26 | 208.52 | 2.8 |
| h10_40_0_1 | 380.51 | 380.51 | 644.64 | 264.13 | 4.5 |
| h10_40_0_2 | 371.65 | 371.818 | 614.5 | 242.85 | 3.8 |
| h10_40_0_3 | 364.31 | 364.31 | 619.24 | 254.93 | 4.7 |
| h10_40_0_4 | 369.18 | 369.18 | 551.8 | 182.62 | 2 |
| h10_40_1_0 | 383.5 | 383.5 | 614.74 | 231.24 | 3 |
| h10_40_1_1 | 402.51 | 402.51 | 665.44 | 262.93 | 3.8 |
| h10_40_1_2 | 393.65 | 393.734 | 678.02 | 284.37 | 5.2 |
| h10_40_1_3 | 386.31 | 386.31 | 650.3 | 263.99 | 4.3 |
| h10_40_1_4 | 391.18 | 391.18 | 600.48 | 209.3 | 2.3 |
| h10_40_2_0 | 411.74 | 413.396 | 640.18 | 228.44 | 2.5 |
| h10_40_2_1 | 433.51 | 433.51 | 743.28 | 309.77 | 5 |
| h10_40_2_2 | 424.65 | 424.734 | 704.28 | 279.63 | 3.9 |
| h10_40_2_3 | 417.31 | 417.31 | 666.2 | 248.89 | 3 |
| h10_40_2_4 | 422.18 | 422.18 | 600.7 | 178.52 | 1.5 |

**Table F.16.** ALNS-STD solutions and break-even ratios for 30-patient instances.

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h30_10_0_0 | 453 | 458.258 | 548.5 | 95.5 | 0.5 |
| h30_10_0_1 | 463.61 | 465.666 | 571.6 | 107.99 | 0.6 |
| h30_10_0_2 | 462.48 | 462.48 | 552.34 | 89.86 | 0.5 |
| h30_10_0_3 | 459.45 | 459.45 | 571.22 | 111.77 | 0.6 |
| h30_10_0_4 | 459.04 | 460.506 | 559.58 | 100.54 | 0.6 |
| h30_10_1_0 | 495.53 | 498.028 | 604.16 | 108.63 | 0.6 |
| h30_10_1_1 | 507.18 | 507.18 | 614.22 | 107.04 | 0.5 |
| h30_10_1_2 | 503.48 | 503.48 | 604.38 | 100.9 | 0.5 |
| h30_10_1_3 | 500.45 | 500.45 | 597.14 | 96.69 | 0.5 |
| h30_10_1_4 | 500.18 | 503.552 | 597.98 | 97.8 | 0.5 |
| h30_10_2_0 | 570.34 | 570.618 | 664.76 | 94.42 | 0.4 |
| h30_10_2_1 | 579.18 | 579.18 | 665.44 | 86.26 | 0.3 |
| h30_10_2_2 | 575.48 | 575.48 | 671.58 | 96.1 | 0.4 |
| h30_10_2_3 | 572.45 | 572.45 | 652.6 | 80.15 | 0.3 |
| h30_10_2_4 | 572.04 | 574.7 | 673.22 | 101.18 | 0.4 |
| h30_20_0_0 | 558.61 | 568.012 | 769.9 | 211.29 | 1.2 |
| h30_20_0_1 | 584.3 | 585.54 | 795.58 | 211.28 | 1.1 |
| h30_20_0_2 | 567.59 | 567.59 | 818.36 | 250.77 | 1.6 |
| h30_20_0_3 | 565.78 | 565.78 | 767.94 | 202.16 | 1.1 |
| h30_20_0_4 | 568.84 | 569.57 | 777.32 | 208.48 | 1.2 |
| h30_20_1_0 | 599.59 | 606.06 | 816.72 | 217.13 | 1.1 |
| h30_20_1_1 | 626.85 | 626.85 | 866.12 | 239.27 | 1.2 |
| h30_20_1_2 | 608.59 | 608.59 | 808.28 | 199.69 | 1 |
| h30_20_1_3 | 602.05 | 605.834 | 785.9 | 183.85 | 0.9 |
| h30_20_1_4 | 609.84 | 610.996 | 808.82 | 198.98 | 1 |
| h30_20_2_0 | 681.03 | 682.112 | 874.98 | 193.95 | 0.8 |
| h30_20_2_1 | 698.62 | 698.804 | 923.62 | 225 | 1 |
| h30_20_2_2 | 680.59 | 680.59 | 894.72 | 214.13 | 0.9 |
| h30_20_2_3 | 678.78 | 678.78 | 849.02 | 170.24 | 0.7 |
| h30_20_2_4 | 681.84 | 681.98 | 883.88 | 202.04 | 0.8 |
| h30_30_0_0 | 660.92 | 674.008 | 959.54 | 298.62 | 1.6 |
| h30_30_0_1 | 695.92 | 701.784 | 1039.02 | 343.1 | 1.9 |
| h30_30_0_2 | 682.78 | 682.78 | 1053.54 | 370.76 | 2.4 |
| h30_30_0_3 | 670.36 | 675.106 | 989.12 | 318.76 | 1.8 |
| h30_30_0_4 | 670.21 | 673.722 | 967.3 | 297.09 | 1.6 |
| h30_30_1_0 | 701.5 | 711.156 | 1045.36 | 343.86 | 1.9 |
| h30_30_1_1 | 739.49 | 742.474 | 1106.12 | 366.63 | 2 |
| h30_30_1_2 | 723.78 | 723.78 | 1047.8 | 324.02 | 1.6 |
| h30_30_1_3 | 714.99 | 717.03 | 996.64 | 281.65 | 1.3 |
| h30_30_1_4 | 715.39 | 715.96 | 1008.44 | 293.05 | 1.4 |

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h30_30_2_0 | 777.77 | 782.312 | 1069.3 | 291.53 | 1.2 |
| h30_30_2_1 | 808.21 | 814.642 | 1163.3 | 355.09 | 1.6 |
| h30_30_2_2 | 795.78 | 795.78 | 1144.22 | 348.44 | 1.6 |
| h30_30_2_3 | 782.59 | 788.15 | 1057.34 | 274.75 | 1.1 |
| h30_30_2_4 | 783.21 | 790.366 | 1074.72 | 291.51 | 1.2 |
| h30_40_0_0 | 766.48 | 781.078 | 1163.52 | 397.04 | 2.1 |
| h30_40_0_1 | 825.43 | 825.43 | 1249.28 | 423.85 | 2.1 |
| h30_40_0_2 | 795.25 | 795.25 | 1274.94 | 479.69 | 3 |
| h30_40_0_3 | 774.98 | 783.276 | 1179.64 | 404.66 | 2.2 |
| h30_40_0_4 | 783.67 | 785.854 | 1190.08 | 406.41 | 2.2 |
| h30_40_1_0 | 813.49 | 824.638 | 1253.14 | 439.65 | 2.4 |
| h30_40_1_1 | 854.28 | 863.888 | 1328.04 | 473.76 | 2.5 |
| h30_40_1_2 | 836.25 | 836.25 | 1273.12 | 436.87 | 2.2 |
| h30_40_1_3 | 817.26 | 824.532 | 1224.14 | 406.88 | 2 |
| h30_40_1_4 | 824.67 | 826.168 | 1217.12 | 392.45 | 1.8 |
| h30_40_2_0 | 886.1 | 898.558 | 1298.9 | 412.8 | 1.7 |
| h30_40_2_1 | 938.82 | 941.416 | 1413.4 | 474.58 | 2 |
| h30_40_2_2 | 908.25 | 908.25 | 1348.32 | 440.07 | 1.9 |
| h30_40_2_3 | 889.25 | 896.53 | 1306.24 | 416.99 | 1.8 |
| h30_40_2_4 | 900.97 | 905.218 | 1247.14 | 346.17 | 1.2 |

**Table F. 17.** ALNS-STD solutions and break-even ratios for 50-patient instances.

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h50_10_0_0 | 746.2 | 748.994 | 909.82 | 163.62 | 0.6 |
| h50_10_0_1 | 737.77 | 740.464 | 930.92 | 193.15 | 0.7 |
| h50_10_0_2 | 750.24 | 751.108 | 942.04 | 191.8 | 0.7 |
| h50_10_0_3 | 728.15 | 728.83 | 889.4 | 161.25 | 0.6 |
| h50_10_0_4 | 743.15 | 743.412 | 913.76 | 170.61 | 0.6 |
| h50_10_1_0 | 883.15 | 885.794 | 1070.26 | 187.11 | 0.5 |
| h50_10_1_1 | 877.17 | 879.13 | 1072.84 | 195.67 | 0.6 |
| h50_10_1_2 | 886.61 | 888.376 | 1053.3 | 166.69 | 0.5 |
| h50_10_1_3 | 866.48 | 866.726 | 1021 | 154.52 | 0.4 |
| h50_10_1_4 | 880.15 | 880.15 | 1030.02 | 149.87 | 0.4 |
| h50_10_2_0 | 1035.15 | 1039.146 | 1211.42 | 176.27 | 0.4 |
| h50_10_2_1 | 1028.57 | 1029.176 | 1219.42 | 190.85 | 0.5 |
| h50_10_2_2 | 1038.61 | 1040.694 | 1216.24 | 177.63 | 0.4 |
| h50_10_2_3 | 1016.5 | 1017.502 | 1183 | 166.5 | 0.4 |
| h50_10_2_4 | 1032.15 | 1032.462 | 1207.66 | 175.51 | 0.4 |
| h50_20_0_0 | 937.06 | 943.964 | 1267.5 | 330.44 | 1.1 |

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h50_20_0_1 | 926.25 | 927.85 | 1299.14 | 372.89 | 1.3 |
| h50_20_0_2 | 945.51 | 947.582 | 1301.56 | 356.05 | 1.2 |
| h50_20_0_3 | 902.41 | 904.42 | 1176.6 | 274.19 | 0.9 |
| h50_20_0_4 | 932.87 | 932.992 | 1280.86 | 347.99 | 1.2 |
| h50_20_1_0 | 1074.06 | 1078.708 | 1406.52 | 332.46 | 0.9 |
| h50_20_1_1 | 1062.65 | 1065.992 | 1382.12 | 319.47 | 0.9 |
| h50_20_1_2 | 1081.11 | 1084.184 | 1465.96 | 384.85 | 1.1 |
| h50_20_1_3 | 1041.12 | 1041.964 | 1331.9 | 290.78 | 0.8 |
| h50_20_1_4 | 1069.87 | 1070.314 | 1383.84 | 313.97 | 0.8 |
| h50_20_2_0 | 1232.82 | 1234.888 | 1591.36 | 358.54 | 0.8 |
| h50_20_2_1 | 1214.65 | 1217.674 | 1588.36 | 373.71 | 0.9 |
| h50_20_2_2 | 1232.91 | 1235.188 | 1602.74 | 369.83 | 0.9 |
| h50_20_2_3 | 1191.41 | 1192.21 | 1465.66 | 274.25 | 0.6 |
| h50_20_2_4 | 1221.87 | 1222.142 | 1544.46 | 322.59 | 0.7 |
| h50_30_0_0 | 1127.57 | 1134.43 | 1569.1 | 441.53 | 1.3 |
| h50_30_0_1 | 1113.81 | 1114.642 | 1598.98 | 485.17 | 1.5 |
| h50_30_0_2 | 1146.2 | 1148.628 | 1679.3 | 533.1 | 1.7 |
| h50_30_0_3 | 1083.84 | 1083.84 | 1504.66 | 420.82 | 1.3 |
| h50_30_0_4 | 1126.6 | 1126.748 | 1621.08 | 494.48 | 1.6 |
| h50_30_1_0 | 1264.09 | 1270.016 | 1723.9 | 459.81 | 1.1 |
| h50_30_1_1 | 1245.67 | 1249.818 | 1746.08 | 500.41 | 1.3 |
| h50_30_1_2 | 1282.39 | 1286.464 | 1808.54 | 526.15 | 1.4 |
| h50_30_1_3 | 1220.84 | 1220.84 | 1625.76 | 404.92 | 1 |
| h50_30_1_4 | 1263.6 | 1263.748 | 1744.46 | 480.86 | 1.2 |
| h50_30_2_0 | 1415.99 | 1417.878 | 1836.42 | 420.43 | 0.8 |
| h50_30_2_1 | 1398.58 | 1400.946 | 1938.74 | 540.16 | 1.3 |
| h50_30_2_2 | 1435.2 | 1437.736 | 1980.06 | 544.86 | 1.2 |
| h50_30_2_3 | 1372.84 | 1372.84 | 1764.08 | 391.24 | 0.8 |
| h50_30_2_4 | 1415.97 | 1415.972 | 1931.36 | 515.39 | 1.1 |
| h50_40_0_0 | 1320.89 | 1331.308 | 1871.68 | 550.79 | 1.4 |
| h50_40_0_1 | 1312.33 | 1314.804 | 1971.42 | 659.09 | 2 |
| h50_40_0_2 | 1344.03 | 1347 | 2012.02 | 667.99 | 2 |
| h50_40_0_3 | 1260.57 | 1260.57 | 1774.16 | 513.59 | 1.4 |
| h50_40_0_4 | 1316.06 | 1316.356 | 1950.78 | 634.72 | 1.9 |
| h50_40_1_0 | 1455.25 | 1461.442 | 2047.46 | 592.21 | 1.4 |
| h50_40_1_1 | 1442.72 | 1449.804 | 2071.16 | 628.44 | 1.5 |
| h50_40_1_2 | 1480.74 | 1485.04 | 2144.36 | 663.62 | 1.6 |
| h50_40_1_3 | 1397.57 | 1397.57 | 1914.2 | 516.63 | 1.2 |
| h50_40_1_4 | 1456.25 | 1456.724 | 2080.46 | 624.21 | 1.5 |
| h50_40_2_0 | 1607.25 | 1614.2 | 2287.3 | 680.05 | 1.5 |
| h50_40_2_1 | 1596.03 | 1605.192 | 2292.64 | 696.61 | 1.5 |
| h50_40_2_2 | 1629.6 | 1639.234 | 2352.22 | 722.62 | 1.6 |

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h50_40_2_3 | 1549.86 | 1550.606 | 2056.96 | 507.1 | 1 |
| h50_40_2_4 | 1608.71 | 1608.71 | 2290.88 | 682.17 | 1.5 |

**Table F. 18.** ALNS-STD solutions and break-even ratios for 100-patient instances.

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h100_10_0_0 | 1581.67 | 1589.786 | 1975.94 | 394.27 | 0.7 |
| h100_10_0_1 | 1562.52 | 1565.392 | 2051.56 | 489.04 | 0.9 |
| h100_10_0_2 | 1580.38 | 1585.93 | 2041.64 | 461.26 | 0.8 |
| h100_10_0_3 | 1578.2 | 1580.2 | 2013.56 | 435.36 | 0.8 |
| h100_10_0_4 | 1601.76 | 1604.676 | 1967.94 | 366.18 | 0.6 |
| h100_10_1_0 | 1914.49 | 1923.402 | 2382.64 | 468.15 | 0.6 |
| h100_10_1_1 | 1902.53 | 1905.818 | 2326.82 | 424.29 | 0.6 |
| h100_10_1_2 | 1917.37 | 1921.808 | 2388.9 | 471.53 | 0.7 |
| h100_10_1_3 | 1920.82 | 1924.34 | 2327.8 | 406.98 | 0.5 |
| h100_10_1_4 | 1945.25 | 1947.224 | 2377.38 | 432.13 | 0.6 |
| h100_10_2_0 | 1999.24 | 2007.968 | 2492.14 | 492.9 | 0.7 |
| h100_10_2_1 | 1985.6 | 1988.07 | 2413.36 | 427.76 | 0.5 |
| h100_10_2_2 | 2000.53 | 2004.33 | 2480.8 | 480.27 | 0.6 |
| h100_10_2_3 | 1998.01 | 2003.274 | 2457.34 | 459.33 | 0.6 |
| h100_10_2_4 | 2014.43 | 2023.398 | 2477.34 | 462.91 | 0.6 |
| h100_20_0_0 | 1969.03 | 1981.914 | 2657.8 | 688.77 | 1.1 |
| h100_20_0_1 | 1934.91 | 1948.976 | 2681.96 | 747.05 | 1.3 |
| h100_20_0_2 | 1970.49 | 1979.106 | 2611.18 | 640.69 | 1.0 |
| h100_20_0_3 | 1969.34 | 1977.528 | 2629.6 | 660.26 | 1.0 |
| h100_20_0_4 | 1994.69 | 2011.222 | 2717.9 | 723.21 | 1.1 |
| h100_20_1_0 | 2304.3 | 2325.934 | 3024.92 | 720.62 | 0.9 |
| h100_20_1_1 | 2281.08 | 2293.752 | 3003.9 | 722.82 | 0.9 |
| h100_20_1_2 | 2311.35 | 2319.314 | 3036.4 | 725.05 | 0.9 |
| h100_20_1_3 | 2303.47 | 2315.992 | 3078.32 | 774.85 | 1.0 |
| h100_20_1_4 | 2340.27 | 2346.596 | 3090.96 | 750.69 | 0.9 |
| h100_20_2_0 | 2393.9 | 2406.694 | 3175.98 | 782.08 | 1.0 |
| h100_20_2_1 | 2362.11 | 2370.542 | 3134.16 | 772.05 | 1.0 |
| h100_20_2_2 | 2399.61 | 2403.952 | 3139.24 | 739.63 | 0.9 |
| h100_20_2_3 | 2385.63 | 2400.682 | 3082.96 | 697.33 | 0.8 |
| h100_20_2_4 | 2417.54 | 2427.548 | 3173.98 | 756.44 | 0.9 |
| h100_30_0_0 | 2365.8 | 2373.264 | 3273.16 | 907.36 | 1.2 |
| h100_30_0_1 | 2330.76 | 2339.942 | 3398.24 | 1067.48 | 1.7 |
| h100_30_0_2 | 2370.46 | 2382.284 | 3241.28 | 870.82 | 1.2 |
| h100_30_0_3 | 2352.21 | 2373.962 | 3191.18 | 838.97 | 1.1 |
| h100_30_0_4 | 2413.79 | 2422.82 | 3398.52 | 984.73 | 1.4 |
| h100_30_1_0 | 2688.06 | 2712.556 | 3702.12 | 1014.06 | 1.2 |
| h100_30_1_1 | 2668.54 | 2686.552 | 3713.72 | 1045.18 | 1.3 |
| h100_30_1_2 | 2698.58 | 2711.902 | 3647.28 | 948.7 | 1.1 |
| h100_30_1_3 | 2700.64 | 2713.372 | 3586.44 | 885.8 | 1.0 |
| h100_30_1_4 | 2756.39 | 2767.222 | 3735.9 | 979.51 | 1.1 |
| h100_30_2_0 | 2774.43 | 2785.114 | 3875.58 | 1101.15 | 1.3 |
| h100_30_2_1 | 2761.99 | 2768.014 | 3829.38 | 1067.39 | 1.3 |
| h100_30_2_2 | 2770.29 | 2796.816 | 3692.94 | 922.65 | 1.0 |
| h100_30_2_3 | 2781.12 | 2793.006 | 3736.7 | 955.58 | 1.0 |
| h100_30_2_4 | 2822.4 | 2839.694 | 3783.46 | 961.06 | 1.0 |

| Instance | Best-found | Avg. | ALNS-VS | ADD | $BER$ |
|---|---|---|---|---|---|
| h100_40_0_0 | 2746.65 | 2768.802 | 3872.08 | 1125.43 | 1.4 |
| h100_40_0_1 | 2689.58 | 2713.964 | 3937.38 | 1247.8 | 1.7 |
| h100_40_0_2 | 2772.4 | 2788.034 | 4027.06 | 1254.66 | 1.7 |
| h100_40_0_3 | 2758.07 | 2768.694 | 3882.64 | 1124.57 | 1.4 |
| h100_40_0_4 | 2813.14 | 2845.296 | 4122.08 | 1308.94 | 1.7 |
| h100_40_1_0 | 3091.39 | 3099.684 | 4447.4 | 1356.01 | 1.6 |
| h100_40_1_1 | 3061.43 | 3079.758 | 4386.1 | 1324.67 | 1.5 |
| h100_40_1_2 | 3120.62 | 3139.544 | 4396.34 | 1275.72 | 1.4 |
| h100_40_1_3 | 3090.52 | 3098.836 | 4295.88 | 1205.36 | 1.3 |
| h100_40_1_4 | 3167.35 | 3179.958 | 4479.1 | 1311.75 | 1.4 |
| h100_40_2_0 | 3171.75 | 3193.064 | 4545.96 | 1374.21 | 1.5 |
| h100_40_2_1 | 3136.95 | 3164.082 | 4480.66 | 1343.71 | 1.5 |
| h100_40_2_2 | 3188.39 | 3212.272 | 4612.04 | 1423.65 | 1.6 |
| h100_40_2_3 | 3151.92 | 3170.768 | 4369.82 | 1217.9 | 1.3 |
| h100_40_2_4 | 3220.08 | 3245.284 | 4668.38 | 1448.3 | 1.6 |