Home Hospitalization: A Bi-objective problem considering Travel Time and Continuity of Care, and accounting for Workload Balance

The case study of Hospital Garcia de Orta

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Declaração

Declaro que o presente documento é um trabalho original da minha autoria e que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Abstract

The increase in life expectancy has resulted in an aging population with more need for hospital care. Therefore, hospitals have noticed higher pressure on capacity and costs. These factors have encouraged the emergence of new alternatives to conventional hospitalization, which is the case of Home Hospitalization. In Portugal, this alternative emerged in 2015 and has shown promising results regarding patient satisfaction, mortality rate, and direct costs. Even so, this service implies the consideration of complex logistical aspects that are currently solved manually.

A bi-objective optimization problem is developed, aiming to minimize Travel Times and maximize Continuity of Care while ensuring Workload Balance. The purpose is to account for the three stakeholders' perspectives: managers, patients, and care workers. In the proposed model, nurses and physicians are assigned to teams that travel by car to locations representing the patients' homes, respecting some constraints. The epsilon-constraint method is used to find the approximate Pareto front of the two conflicting objectives. The trade-off between the objectives is analyzed through the computational results. Two different approaches are discussed to help decide on the Pareto front's best solution: Crowding distance and TOPSIS.

Based on the real-world instances provided by the hospital under study, the proposed method can provide, on average, a reduction in Travel Time by 7.09%, an increase in Continuity of Care of 35.18% and an increase of 65.73% on Workload Balance. Thus, the three stakeholders' perspectives can be improved significantly with the use of the model. Numerical experiments are also conducted in literature instances.

Keywords: Home Health Care; Home Hospitalization; Staff Scheduling; Staff Routing; Pareto front; Multi-Objective Optimization

Resumo

O aumento da esperança média de vida tem resultado numa população mais envelhecida e com maior necessidade de cuidados hospitalares. Por conseguinte, os hospitais têm sofrido uma maior pressão, tanto ao nível de recursos como de custos. Estes fatores incentivaram o aparecimento de alternativas ao internamento convencional, como é o caso da Hospitalização Domiciliária.

Um modelo de optimização bi-objectivo é desenvolvido, com o objectivo de minimizar os Tempos de Deslocação e maximizar a Continuidade dos Cuidados, assegurando ao mesmo tempo o Equilíbrio da Carga de Trabalho. O objectivo é considerar os interesses das três partes interessadas envolvidas - gestores, pacientes e profissionais de saúde. No modelo proposto, enfermeiros e médicos são distribuídos por equipas que viajam de carro para um conjunto de locais que representam as casas dos pacientes, respeitando algumas restrições.

O método epsilon-constraint é utilizado para encontrar a fronteira de Pareto aproximada dos dois objectivos em conflito. Depois, são discutidos dois métodos diferentes para ajudar na decisão da melhor solução da fronteira de Pareto: *Crowding distance* e TOPSIS.

Com base em instâncias reais fornecidas pelo hospital em estudo, o método proposto é capaz de proporcionar, em média, uma redução de Tempos de Deslocação de 7,09%, um aumento da Continuidade dos Cuidados de 35,18% e um melhoramento de 65,73% no Balanço da Carga de Trabalho, simultaneamente. Assim, as perspectivas das três partes interessadas podem ser significativamente melhoradas com a utilização do modelo. Experiências computacionais foram também conduzidas em instâncias da literatura.

Keywords: Cuidados de Saúde em casa; Hospitalização Domiciliária; Roteamento; Fronteira de Pareto; Optimização Multi-Objectivo

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Acronyms

ACO Ant Colony Optimization. 31, 69

ARS *Administrações Regionais de Saúde* (Portuguese Regional Health Administrations). 11

B&P Branch-and-Price. 30

BOOP Bi-Objective Optimization Problem. 46, 48

CP Constraint Programming. 31

DGS *Direção-Geral da Saúde* (Portuguese Directorate-General of Health). 11

GDP Gross Domestic Product. 6, 10

HC Home Care. 6

HGO Hospital Garcia de Orta. 1–5, 10–17, 19, 20, 35, 43, 53, 57, 63, 65, 71, 72

HH Home Hospitalization. 1–5, 7–9, 11, 12, 14, 15, 17–19, 21, 34, 35, 37, 41, 51, 69, 71, 72

HHC Home Health Care. 2–8, 19, 21–29, 31, 33, 34, 43, 64, 69, 71

HHCRSP Home Health Care Routing and Scheduling Problem. 24, 33, 35, 44, 64

HHU Home Hospitalization Unit. 1–3, 5, 11–20, 33, 35, 36, 43, 44, 51, 53, 54, 56, 61, 69, 71, 72

INE *Instituto Nacional de Estatística* (Portuguese National Institute of Statistics). 9

LNS Large Neighborhood Search. 31, 32

LTC Long-Term Care. 6, 8–10

MA Memetic Algorithm. 31, 69

MCDM Multiple Criteria Decision-Making. 45, 46, 50, 51, 59

MILP Mixed-Integer Linear Programming. 37, 42, 53

MO Multiple-Objective. 44

MOOP Multiple-Objective Optimization Problem. 45–48

OECD Organization for Economic Cooperation and Development. 1, 2, 6, 9, 10, 19

PCT Primary Care Team. 15

PSO Particle Swarm Optimization. 31

RNCCI *Rede Nacional de Cuidados Continuados Integrados* (Portuguese National Network for Long-term Care). 10, 13

RNCP *Rede Nacional de Cuidados Paliativos* (Portuguese National Network of Palliative Care). 10

SA Simulated Annealing. 31

SNS *Serviço Nacional de Saúde* (Portuguese National Health Service). 11, 12

SOOP Single-Objective Optimization Problem. 45–47, 54

SPH Set Partitioning Heuristic. 31

SPP Set Partitioning Problem. 30, 31

TOPSIS Technique for Order of Preference by Similarity to Ideal Solution. xiv, 46, 50, 51, 57, 59, 61, 69, 86, 88

TS Tabu Search. 31

VNS Variable Neighborhood Search. 31, 69

VRP Vehicle Routing Problem. 24, 27, 28, 35, 39, 55, 69

VRPTW Vehicle Routing Problem with Time Windows. 24, 28, 31

WHO World Health Organization. 5

Chapter 1

Introduction

This chapter introduces the present dissertation. Section 1.1 provides a context and motivation for the problem under study. In section 1.2, the proposed research objectives are listed while section 1.3 presents the research methodology. At the end of the chapter (section 1.4), the document structure is provided.

1.1 Background and Motivation

The demand for hospital care has grown considerably due to the increase in life expectancy and the aging population. The average life expectancy at birth across Organization for Economic Cooperation and Development (OECD) countries was 80.7 years in 2017, ten years higher than in 1970 (OECD, 2019). Additionally, the share of the population aged 65 years and older has nearly doubled from 9% in 1960 to more than 17% in 2017. As a consequence, more people around the world need ongoing health and social care. Indeed, the aging society led to an increase in the prevalence of chronic diseases in patients, resulting in overcrowding of emergency services.

In order to relieve the pressure in the acute hospital beds, together with an attempt to improve patient's satisfaction and expectations, some countries are adopting an alternative approach to conventional hospitalization. This alternative is called Home Hospitalization (HH). HH is defined as the clinical activity, which allows health care professionals to perform diagnostic and therapeutic procedures, usually associated with acute inpatient care, at the patient's home (Cheng et al., 2009). The evidence shows that this alternative enables to improve the life quality of patients and avoid the risk of hospital infections.

Hospital Garcia de Orta (HGO) implemented in November 2015 the first hospital unit in Portugal specifically dedicated to HH. In addition to patient and family satisfaction, this alternative has shown to be economically attractive as well. The cost savings for using HH were 45.83% in 2017 and 34.72% in 2018 (HGO, 2019b). The HGO's Home Hospitalization Unit (HHU) aims to increase the number of patients served each day, making more beds available for the hospital. However, to increase the number of patients served, the efficiency of operations and decisions must be improved. For instance, routing and scheduling decisions are made manually, taking approximately 30-45 minutes every morning, resulting in high organizational efforts (i.e., waste of time and resources) and potentially sub-optimal solutions.

Moreover, all these decisions are based on the staff's experience with no systematic or decision support.

Planning decisions in health care organizations require a consideration of three key stakeholders: patients, care workers and managers. Nevertheless, these three key stakeholders have interests that most of the time come into conflict: quality of the service, workload balance and low costs, respectively. Considering that all the planning is currently done manually by HGO, it is difficult to account for all aspects simultaneously. As a result, the main focus of the HGO's HHU has been in containing costs.

The literature on HH is scarce, especially in logistical terms. However, another alternative with the same broad objectives of combating demographic shifts and with the same type of logistical operations is called Home Health Care (HHC). It is also about providing health care services in the patient's home. Nonetheless, HH concerns patients with acute or chronic pathologies who would require inpatient care in the absence of this service. By contrast, the literature on HHC regarding planning decisions is quite extensive, and it is possible to show that OECD countries are betting on this alternative. In this way, the concept of HHC is also approached in this dissertation since the operations and logistics planning' decisions are roughly the same.

1.2 Research Objectives

The main goal of this dissertation is to improve the planning decisions of the HGO's HHU, considering the main challenges faced by this unit. For this purpose, the objective is to develop a decision support tool for scheduling and routing decisions, which can be generalized for other HHUs. The decision support tool should focus on the efficiency and on the quality of the service, showing the impact of the different features in the planning decisions. Therefore, the main objectives of this dissertation are to:

1. Characterize the concept of HH; describe the HGO's HHU and identify the main challenges when planning the schedules and routes;

2. Elaborate a literature review on planning decisions in HHC with a particular focus on operational decisions regarding scheduling and routing; identify the main features used in the different models as well as objectives and solutions methodologies considered;

3. Contributing to the existing literature with a mathematical model focused on HH and its specific characteristics; develop a solution approach which enables an insightful study of the trade-off between the considered objectives of the proposed model;

4. Provide managerial insights and recommendations to the HGO's HHU regarding planning decisions.

1.3 Research Methodology

To achieve the presented objectives, the methodology in the diagram of Figure 1.1 is proposed.

- **Stage 1 – Problem Context and definition –** In the first stage, the problem to be addressed is described. This stage introduces the concepts of HHC and HH and characterizes the HHU of

HGO's, which is the case under study in this dissertation. The planning currently done by the unit and the main challenges faced are described.

- **Stage 2 – Literature Review –** The objective of this stage is to gain a comprehensive knowledge of the HHC planning decisions, focusing mainly on scheduling and routing. The most common formulations in the field are studied to serve as a guide and inspiration for developing the decision support tool. Thus, an overview of the features and solutions methodologies used in the literature is provided.

- **Stage 3 – Model Development and Solution Approach–** In this stage, considering the problem definition and the literature review, a mathematical model is developed according to the characteristics of the HGO's HHU. The objectives are to reduce Travel Time and maximize Continuity of Care while accounting for Workload Balance within teams. Furthermore, a solution approach is proposed to couple with the developed model.

- **Stage 4 - Data Collection and Model Validation -** The purpose of this step is to collect and process data on the HHU operations (i.e., daily data of patients visits) and validate the model with the collaboration of the HGO's HHU. Additionally, literature instances were also used to evaluate the model applicability.

- **Stage 5 – Computational Experiments and Results Analysis –** This is the final stage of the methodology, where computational experiments are performed in the data collected in the previous step. This stage aims to understand the impact of the various features used in the model and if the intended effects are being achieved - decrease Travel Time, increase Continuity of Care, and ensure Workload Balance. Thus, results are analyzed, and the main conclusions and managerial insights are discussed.

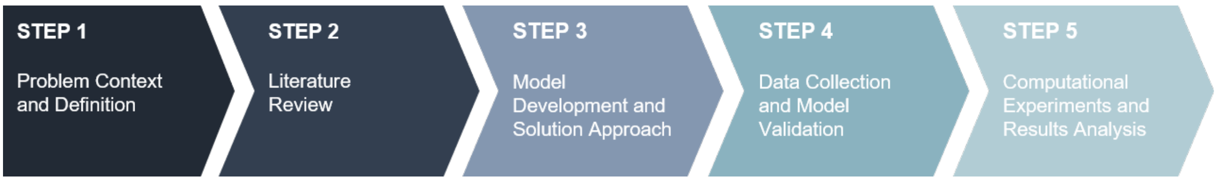

Figure 1.1: Stages of the proposed methodology

1.4 Document Structure

The present dissertation is structured into six chapters:

- **Chapter 1 – Introduction -** Corresponds to the present chapter and aims to contextualize the problem and explain the motivation of this study. The main objectives are highlighted, and the structure of the dissertation is detailed.

- **Chapter 2 – Problem definition -** This chapter explains the concept of HHC and its growing importance around the world. Then, HH is also presented and the Portuguese situation concerning this alternative. The case of HGO, the pioneers of HH in Portugal, is analyzed. The chapter ends with the problem description.

- **Chapter 3 – Literature review -** As the literature review on HH is almost nonexistent, the study focuses on the HHC literature, aiming to transport strategies for HH. Thus, this chapter presents a detailed literature review in terms of HHC planning decisions.
- **Chapter 4 – Mathematical Model and Solution Approach -** Chapter 4 describes the proposed mathematical model considering the problem under study and the literature's insights. A solution approach is also detailed to help in the process of decision-making.
- **Chapter 5 – Numerical Experiments -** This chapter presents the numerical experiments done with the developed mathematical model and discusses the main results obtained for the HHU. The performance of the model is also tested via application in instances derived from the literature.
- **Chapter 6 – Conclusions and Future Research -** Being the final chapter of the dissertation, the most relevant results and conclusions are presented. In addition, it identifies some limitations of the study and opportunities for future research.

Chapter 2

Problem Definition

This chapter describes and defines the problem under study. Section 2.1 starts by introducing the concept of HHC and the potential of HHC-based services due to demographic population shifts. Then, section 2.2 describes the concept of HH, an alternative that also emerged in the context of an aging population. An overview of the HH in Portugal is presented in section 2.3. Section 2.4 contextualizes HGO, the first hospital to implement HH in Portugal, and introduces some figures concerning the HHU activity. The chapter ends by describing the problem under study (section 2.5) and with a conclusion of the chapter in section 2.6.

2.1 Home Health Care

The demand for hospital care has grown considerably due to the increase in life expectancy and the aging population. Services such as HHC have been developed in several countries to provide better life quality to older people and avoid unnecessary hospitalizations. This section explains the history and the concept of HHC (subsection 2.1.1) and finalizes by highlighting the demographic shifts which are demanding a change in the care that is provided by health care systems (subsection 2.1.2).

2.1.1 History and definition

The idea of HHC appeared for the first time in 1947, in the United States, with the experience *Home Care* at the Montefiore Hospital in New York, after World War II (Mitchell E. et al., 1965). The aim was to decongest the hospital while creating a more favorable psychological environment for the patient and overcome the difficulties of social strata that at that time lacked health insurance to cover conventional hospitalization (Gutiérrez, 2014). During 1960, France, Switzerland, Germany, the United Kingdom, and Canada also adopted this model (Gutiérrez, 2014; HGO, 2018). In 1996, the World Health Organization (WHO) regional committee for Europe recognized the development of HHC. However, there is no single or uniform history of the HHC services across Europe. Countries have followed different paths and give rise to various policies and provisions, resulting in a mix of approaches and strategies for funding and organizing HHC services (WHO, 2008).

In the literature, the concept of HHC also appears in the context of Home Care (HC). Although these two terms have been addressed interchangeably in the literature, they represent two different problems (Mosquera et al., 2019). HC is a generic term that includes medical, paramedical, and social services provided to patients who require long and regular care in the comfort of their homes. It can involve everyday activities such as bathing, dressing, eating, monitoring daily medication, and accompanying a patient to social events (Bashir et al., 2012; Hulshof et al., 2012). By contrast, the concept of HHC refers to patients recovering from an illness or injury. Thus, the difference relies on the nature of the service provided at home. An example of an HHC service is the nursing homes that concern nurses periodically traveling to patients' homes and providing medical services. As demand is becoming increasingly complex, mixed services (i.e., a service that provides social care and health care) are becoming more prevalent (Genet et al., 2012).

Even though the concepts of HHC and HC are quite old, a uniform description of the processes does not exist. The reason is that health care systems vary among countries due to health policies, funding structures, and culture. Consequently, each country has its organization (Bashir et al., 2012; Gutiérrez, 2014).

2.1.2 Demographic shifts and the potential of Home Health Care

Demographic shifts in countries around the world have resulted in increasing interest in HHC. Across OECD countries, on average, the share of the population aged 65 years and older has nearly doubled from less than 9% in 1960 to more than 17% in 2017. Furthermore, this percentage is projected to continue to increase in the coming decades. This increasing proportion of older people is linked to declining fertility rates and longer life expectancies. Indeed, the average life expectancy at birth across OECD countries was 80.7 years in 2017, ten years higher than in 1970 (OECD, 2019). Thus, more people need ongoing health and social care and, if other alternatives are not available, is expected an increasing pressure on hospital beds. In 2017, the average number of hospital beds per 1,000 people was 4.7 in OECD countries, and the average occupancy rate of acute care beds was 75%. However, increasing the number of hospital beds leads to a higher number of admissions meaning that merely increasing the number of beds does not solve the overcrowding problems in hospitals (OECD, 2019).

Long-Term Care (LTC) services, which include nursing homes and LTC living facilities, aim to provide care to the older population and, by consequence, avoid hospital congestions. Considering that most people in need of LTC prefer to stay in their homes, OECD countries have been investing in HHC services. As a result, in 2017, 68% of the LTC recipients were receiving care at home. Compared to the other health care services, LTC services have seen the highest growth in recent years when looking to out-of-pocket spending on health in OECD countries (Figure 2.1). The total government/compulsory spending on LTC, including both social and health care, accounted on average for 1.7% of Gross Domestic Product (GDP) in OECD countries. Although, only around one-third of the expenditure on LTC-health was home-based LTC (OECD, 2019).

Along with the demographic shifts and government spending, societal developments may also contribute to the growth of HHC. The fact that the patient is being cared for at home brings comfort, security, and privacy. For this reason, more people would prefer to stay in their home (Bashir et al., 2012). Ad-

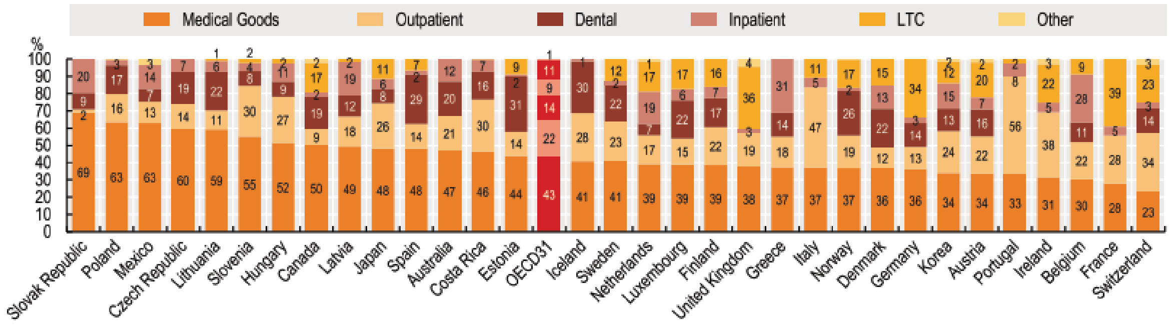

Figure 2.1: Out-of-pocket spending on health, by type of services, in 2017 (OECD, 2019)

ditionally, the provision of services in patients' homes is typically more cost-effective than in institutions (Genet et al., 2012). On the whole, HHC has been proving to be a fast-growing sector in health care due to several motivations as the aging population, preferences of patients, and the continuous pressure of governments to contain health costs. However, at some point, people will require services that cannot be provided by nursing homes and may need specific care that only a hospital can provide. As a consequence, more structures and efforts need to emerge to respond to the increasing aging population.

2.2 Home Hospitalization

In order to relieve the pressure in the acute hospital beds referred to in the last section, together with an attempt to improve patient's satisfaction and expectations, other alternatives despite HHC have been developed. One example is HH, an alternative to conventional hospitalization that many countries are adopting (Cheng et al., 2009). Also known as Hospital at Home and Hospital in the Home, this method has shown positive results. This section explores the concept of HH (subsection 2.2.1) and its scope (subsection 2.2.2). Additionally, the outcomes of this alternative are going to be analyzed (subsection 2.2.3).

2.2.1 Definition

The concept of HH might be originated in France in 1961 with *Hospitalization à Domicile* (Morris, 1983). However, other countries implemented this concept, such as the United States, the Netherlands, Spain, and Australia (Shepperd et al., 2009). HH is generally defined as the clinical activity which allows health care professionals to perform diagnostic and therapeutic procedures, usually associated with acute inpatient care, at the patient's home (Cheng et al., 2009; Quintanilla et al., 2020). The main difference for HHC is that HH concerns patients with acute or chronic pathologies who would require inpatient care in the absence of this service. This mobile service represents an alternative to the conventional hospitalization for patients with specific biological, psychological, and social conditions where health care is guaranteed with the necessary differentiation, complexity, and intensity, equivalent to that which would be provided in a hospital (Di Mascolo et al., 2017; HGO, 2018; Yalcindag et al., 2012).

Since this alternative has been emerging in different countries, and there is no precise definition, different types of HH are described in the literature. The HH structures can be community-based or hospital resourced. Community-based structures are built-in existing community resources such as home health agencies. In these structures, nurses are available for home visits, yet there is no organized input from physicians, working as HHC service. Usually, these structures focus on surgical patients who are sent home early in the postoperative period. By contrast, hospital resourced structures have hospital staff making domiciliary visits, delivering hospital-level care at the patient's home with the physicians' input always available. Therefore, ensuring the same care that the patients would receive inside of a hospital (Cheng et al., 2009; Shepperd et al., 2009).

2.2.2 Scope

The literature generally refers to two possible HH schemes, which can be adopted separately or as a mixed scheme: admission avoidance (i.e., full substitution for conventional hospitalization, even though patients are admitted in the hospital system) and early discharge (i.e., shortened conventional hospitalization) (Caplan et al., 2012). In admission avoidance interventions, patients may be admitted from the emergency department or come directly from the community, referenced by their primary care physician, thus avoiding any physical contact with the hospital. Otherwise, patients may also be discharged early from a particular hospital service and continue to receive hospital care at home - early discharge. Recent HH structures are focusing on avoiding hospital admission to reduce costs and reduce the risk of adverse events associated with conventional hospitalization (**?**). Services such as LTC, end-of-life care at home, and post-discharge from the hospital are excluded from the scope of HH (Gonçalves-Bradley et al., 2017).

The type of patients admitted to HH also change within structures. Some HH structures focus on patients with specific conditions, for example, chronic obstructive pulmonary disease, while other structures have a more broad policy, covering a more extensive range of conditions (**?**). Nevertheless, the general characteristics are illnesses that occur frequently and account for a significant portion of hospitalizations; a straightforward diagnosis that does not need much consultation or invasive testing; and treatments that are well defined and safe to deliver at home. Some examples of these illnesses are heart failure, bronchiectasis, and urinary tract infection(Cheng et al., 2009).

2.2.3 Outcomes and motivations

As mentioned before, demographic shifts, and social trends are motivating alternatives to conventional hospitalization. Indeed, patients' expectations for more personalized care, the emerging of advanced hospital-type technologies, the cost of conventional hospital care, and the increasing demand for inpatient hospital beds have been growing the popularity of HH structures in many countries (Cheng et al., 2009).

Some studies comparing the outcomes (e.g., patient and family members' satisfaction, functional status, clinical complications, length of stay, mortality, hospital readmission, and costs) of HH and acute hospital care have been conducted. Among all reviews, the patients and family members' overall satisfaction has been consistently better in HH. Interviews found that among the reasons for these results are higher levels of personal care, communication with family members, and the fact that being at home is therapeutic (Wilson et al., 2002). Indeed, being treated in the comfort of their home and their family environment creates more favorable psychological conditions for patients (Bashir et al., 2012).

Nevertheless, HH also brings some concerns. For instance, hospitalized patients at home have limited access to technologies and resources in urgent situations. Moreover, it is not possible to have a health care professional always next to the patients. All this may cause apprehension regarding the safety and quality of the service. A study conducted in the United States to assess the clinical feasibility and efficacy of providing acute hospital-level care in patients' home for acutely ill older people conclude that the quality standards were met in similar proportions to acute hospitalization (Leff et al., 2005). This means that care processes, such as oxygen therapy and intravenous antibiotics, were used at similar rates. Moreover, patients treated at home had fewer significant clinical complications related to the need of using sedative medications or incident delirium (defined as acute onset and fluctuating course of symptoms of delirium, inattention, and either disorganized thinking). Additionally, the risk of hospital-acquired infections is reduced considerably (Bashir et al., 2012).

Some outcomes are not conclusive. Regarding mortality and hospital readmission, some reviews conclude HH makes little or no difference (Gonçalves-Bradley et al., 2017; Leff et al., 2005), while other study found a clinically significant reduction in both outcomes (Caplan et al., 2012). Thus, it is not possible to state a conclusion. Concerning the length of stay, the majority of the reviews claim that hospital-acquired infections is reduced considerably(Gonçalves-Bradley et al., 2017; Leff et al., 2005). Finally, regarding economic outcomes, there is no compelling evidence that HH produces cost savings since there are different ways of calculating the costs. However, most reviews estimate lower costs for HH (Shepperd, Iliffe, 2005). In specific, Caplan et al. (2012) and Leff et al. (2005) estimated that the cost of HH was 73.5% and 67.9% of the acute care hospital costs, respectively.

After all, HH provides outcomes that are at least equivalent, if not better, to the outcomes of conventional hospitalization. Thus, one can conclude that providing hospital care at home is possible, safe, and can even bring some advantages.

2.3 Home Hospitalization in Portugal

Portugal is a country that has a significant aged population and does not seem to be investing much in LTC services. Moreover, the aging population pressures hospital admissions and health resources' consumption. HH appears then as a good alternative for the current Portuguese panorama to release the pressure in acute hospital beds and reduce risks associated with hospital admission. This section discusses the health status in Portugal (subsection 2.3.1) and the evolution of HH (subsection 2.3.2).

2.3.1 Health status and Long-Term Care

In 2017, life expectancy at birth in Portugal was 81.5 years (higher than OECD average of 80.7). Similarly, the proportion of older people aged 65 years and older was 21.3% in 2017, 4.3% higher than the OECD average (OECD, 2019). According to *Instituto Nacional de Estatística* (Portuguese National Institute of Statistics) (INE) the life expectancy at the age of 65 in Portugal in 2018 was estimated to be 19.49 years. However, considering the indicator of healthy life years at age 65, the number of healthy years is only 7.3. Thus, the increase in life expectancy does not come along with years lived in good health (INE, 2020).

The proportion of people aged 65 and over who have been hospitalized has shown a growing trend in recent years. In 2018, 43.1% of the patients discharged from Portuguese hospitals were 65 or older. As would be expected, the increase in the number of hospitalizations is in line with the rise in the aging index (i.e., the quotient between the number of people aged 65 and over and the number of people aged between 0 and 14) (Figure 2.2) (INE, 2020).

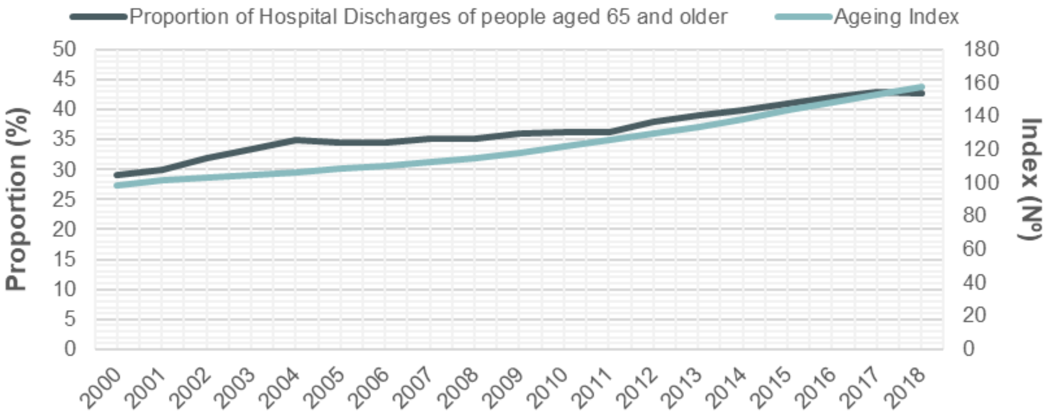

Figure 2.2: Evolution of the proportion of people aged 65 and older discharged from hospital and of the aging index (No.), Portugal, 2000-2018 (INE, 2020)

Nevertheless, as a response to an aged population, some LTC projects such as day centers, nursing homes, and residences for the elderly have been developed. In 2006, due to the lack of resources in LTC and palliative care in the public sector, the *Rede Nacional de Cuidados Continuados Integrados* (Portuguese National Network for Long-term Care) (RNCCI) was created. This network provides three types of services: short-term recovery (associated with hospitals) to provide treatment and clinical supervision to patients that do not need acute hospital care; medium-term care and rehabilitation; and LTC to provide care that will prevent and retard increasing dependency, favoring comfort and quality of life. Later in 2012, the *Rede Nacional de Cuidados Paliativos* (Portuguese National Network of Palliative Care) (RNCP) was created to provide palliative care to ill people, irrespective of their age and pathology, which until then was provided by RNCCI (Simões, Hernández-Quevedo, 2017).

However, when observing the LTC statistics provided by OECD for 2017, it seems that little or nothing is being done to provide a better quality of life for older people in Portugal. Only 1.9% of adults aged 65 and over are receiving LTC, and from this percentage, only 32% receive the LTC at home. Regarding expenditures by government and compulsory insurance, LTC (health and social) only account for 0.5% of the GDP, which is significantly lower than the OECD average of 1.7% (OECD, 2019).

2.3.2 The evolution of Home Hospitalization

Together with the small investment in LTC, the aging population leads to a higher number of hospitalizations in Portugal. To relieve the pressure in acute hospital beds and provide more personalized care to patients, HGO implemented in November 2015 the first hospital unit in Portugal specifically dedicated to

HH. In October 2018, the Secretary of State for Health published the National Strategy for the implementation of HHUs in the *Serviço Nacional de Saúde* (Portuguese National Health Service) (SNS) (Dispatch No. 9323-A/2018 of October 3, 2018), aiming to ensure the harmonization of practices and models of care within the SNS hospital entities. The strategy states that all hospital entities capable of financing an HHU must have started the activity by March 31, 2019. In addition, the *Administrações Regionais de Saúde* (Portuguese Regional Health Administrations) (ARS) must submit a plan for the extension of HHU in the remaining hospitals, which must have been implemented by June 2019. The *Direção-Geral da Saúde* (Portuguese Directorate-General of Health) (DGS) created a clinical orientation norm (Norm No. 020/2018 of December 20, 2018) which define, according to international literature, the list of common eligible pathologies and the general inclusion and exclusion criteria, without compromising the adjustment to the concrete reality of each institution and the local needs of the population.

Since the implementation in Portugal by HGO until its normative institutionalization by DGS, the number of HHUs have consistently increased. In 2019, there were already 25 public hospitals with an HHU (Figure 2.3), and more than 3,000 patients have been assisted – 1,633 of which were assisted by HGO. Hospitals with HHUs are more concentrated in Lisboa and Porto regions, and some districts are not yet covered by this implementation, such as Guarda, Beja, and Évora. Nevertheless, the Portugal Government Budget for 2020 has a financial increase of 1.2 million euros for implementation and reinforcement of HH responses in all SNS entities (Ministério da Saúde, 2020).

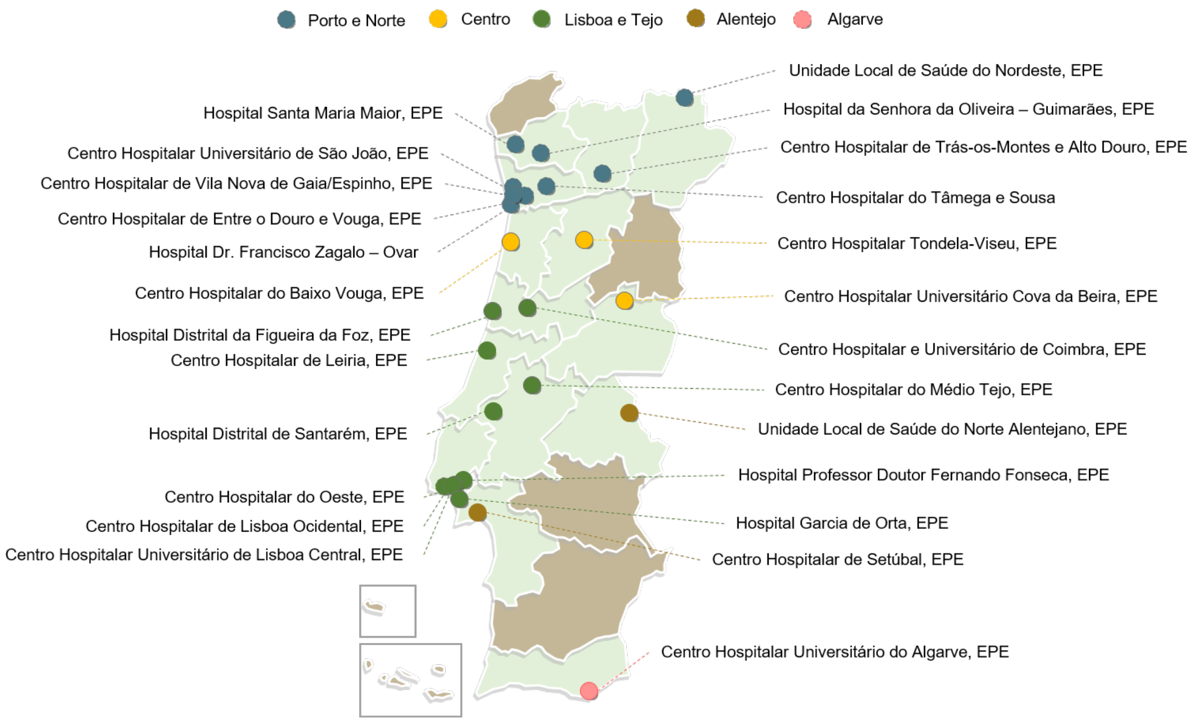

Figure 2.3: Portuguese public hospitals with an HHU in 2019 (Ministério da Saúde, 2018)

The importance of HH has been recognized, and its development has been supported, allowing a rapid expansion of HH over the last few years. Moreover, there is still a high percentage of the number of hospitalizations in Portugal, which can be possibly replaced by HH. Therefore, it is essential to consolidate and extend the HH in the SNS.

2.4 Hospital Garcia de Orta

HGO is the pioneer in the implementation of HH in Portugal and has been active in this service for over four years. This section starts by providing an overview of HGO (subsection 2.4.1) before describing the HHU. In subsection 2.4.2, detailed information about the unit is provided: resources, the process that a patient goes through inside of the unit, statistics, and outcomes of the past years. The section ends by describing the scheduling and routing decisions at HGO (subsection 2.4.3).

2.4.1 Characterization

HGO is a public hospital belonging to the SNS which provides differentiated health care to the population of Almada and Seixal' municipalities. The hospital started its activity in 1991, having initially as the area of influence, beyond Almada and Seixal, also the city of Sesimbra. However, due to the considerable increase in population, in 2013, the hospital redefined its area of direct influence. According to the annual report of 2018, HGO serves an estimated population of 332,299 inhabitants and has 2,691 employees, of whom 397 are physicians and 946 are nurses. In 2018 were registered 292,517 medical appointments and 169,036 emergency admissions. Regarding financial results, the revenues for 2018 were 149,484,070€ (139 million of which were services provided to the SNS), while the expenses were 166,846,358€, making a net result of -17,410,769.97€ (HGO, 2019a). These data are summarized in Table 2.1.

General information	
Total population resident in the area of influence	332 299
Discharged patients (without nursery)	21 360
Total medical appointments	292 517
Number of emergency admissions	169 036
Day centres sessions	10 424
Resources	
Capacity (without nursery) - beds	565
Number of employees	2 691
Financial and economic information (€)	
Share capital	140 780 000 €
Investments	4 018 820.58 €
Net result	-17 410 769.97 €

Table 2.1: Overall activity in 2018 (HGO, 2019a)

HGO has a capacity of 565 beds, plus an average of 10 beds for HH. In addition to this capacity, the hospital also had an average of 10 contingency beds available in 2018. The average occupancy rate was 90.1%, accounting for the contingency beds, which is around 10% above the national average in 2018 (INE, 2020). The number of discharged patients (without nursery) was 21,360, with an average length of stay of 8.9 days. The age range of the treated population (without nursery) was manifestly high, as can be seen in the graph of Figure 2.4. Almost half of the discharged patients (47%) in HGO have 65 years or more.

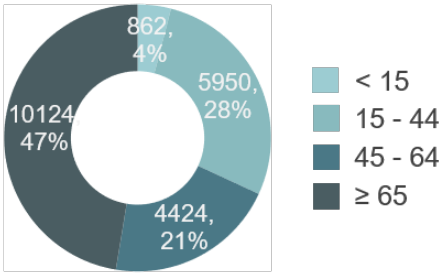

Figure 2.4: Absolute and relative distribution of discharged patients by age group (no nursery) (HGO, 2019a)

The hospital had a growth in the admission of advanced age patients to the emergency department and other hospital services. The high number of elderly residences in the hospital's area of influence is undoubtedly a contributing factor. HGO already uses the RNCCI to relieve the pressure in admissions of acute patients. Despite the improvement seen in recent years regarding the response of the RNCCI, the hospital claims that it was still very insufficient, translating into a high number of days of hospitalization (HGO, 2019a).

2.4.2 Home Hospitalization Unit

To respond to the increasing pressure in acute care, the HGO implemented an HHU on November 16, 2015, as an alternative to conventional hospitalization. With the motto "We take care of you in your home", the unit seeks to provide a more humanized clinical care, minimizing complications inherent to conventional hospitalization (HGO, 2018). The reasons for emerging this unit in the hospital are strongly connected with the five objectives below (HGO, 2018):

1. Humanize care, offering differentiated hospital-level treatment in the comfort of the home;
2. Reduce the rate of complications related to the conventional hospital stay;
3. Bring the hospital closer to the community by developing outpatient medicine and health education activities in the family, the individual, and the community;
4. Promote the functional recovery and autonomy of the patient while stimulating the active participation of the family in the provision of care, preventing rejection and abandonment;
5. Improve access to hospital-level care and to contribute to improving the management of available beds.

The remainder of this section will provide a more detailed description of the unit, precisely the patient flow, resources and capacity, and main outcomes.

Process of the HHU

The process that a patient goes through in the HHU can be seen in Figure 2.5 (OECD, 2019). This process can be divided into two main algorithms: intake algorithm (top left) and tracking and planning algorithm (bottom right).

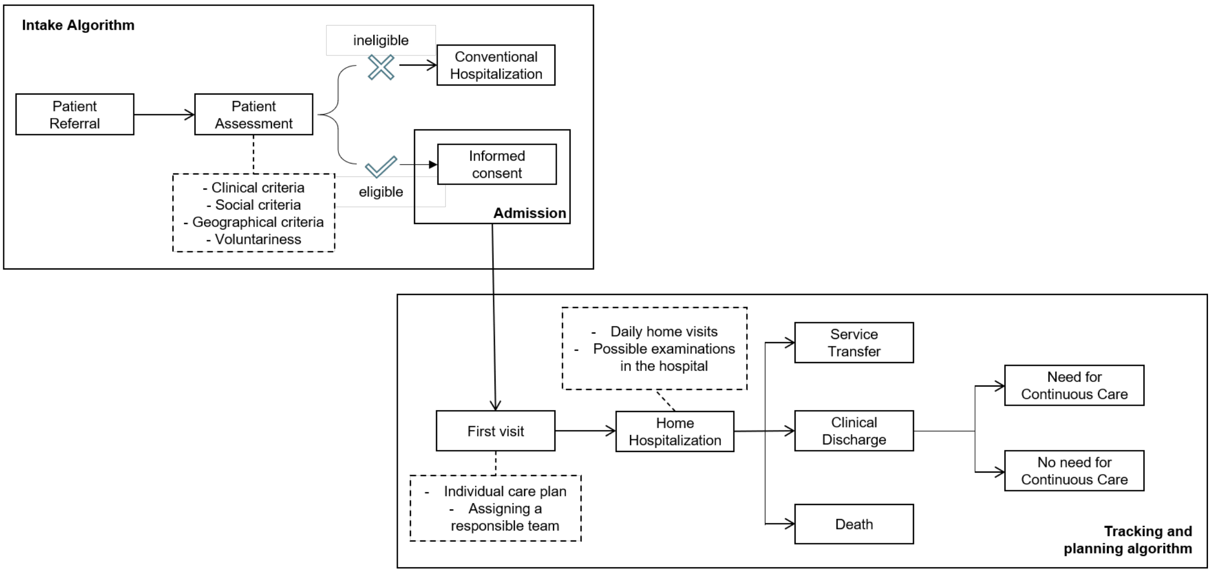

Figure 2.5: Process of a patient in the HHU (adapted from HGO, 2018)

The intake algorithm begins with a patient referral from the emergency department, other hospital services, or the community (e.g., primary care physician). The second case occurs when patients may be discharged early from other services in the hospital after an initial clinical stabilization period and are referred from the wards to the HHU. Thus, HGO adopts a mixed structure of HH with admission avoidance and early discharge. Nevertheless, after being referred, the patient needs to meet the admission criteria for the HHU. Firstly, from a clinical point-of-view, the patient is accessed by a physician. The physician makes the diagnosis of the patient, the medical condition, and the therapeutic needs. Then, regarding social criteria, a social worker assesses whether there are conditions to proceed with the hospitalization, such as minimum living and hygiene conditions and the daily presence of an informal caregiver (i.e., a person, usually a relative, who is at home with the patient during the hospitalization and assists the patient in whatever way is necessary). Patients with acute psychiatric pathology, suicidal ideation, active alcoholism, and homeless are excluded. Furthermore, the patient's residence needs to be in the area of influence of the hospital. Finally, the patient and family need to approve and want the patient to be hospitalized at home.

Figure 2.6 shows some statistics about patients' admission in 2019. Most of the patients were referred by the wards (67%), and only 25% came directly from the emergency department (graph Patient's Origin). The admission rate (i.e., the number of admitted patients compared to the number of referred patients) was 51%, and the primary cause from the 49% rejected cases was due to clinical criteria (61%) as we can see in Figure 2.6 (Reasons for Non-Admission, on the right). The absence of an informal caregiver represents almost 15%.

After the intake algorithm (Figure 2.5, top left), the patient follows the tracking and planning algorithm

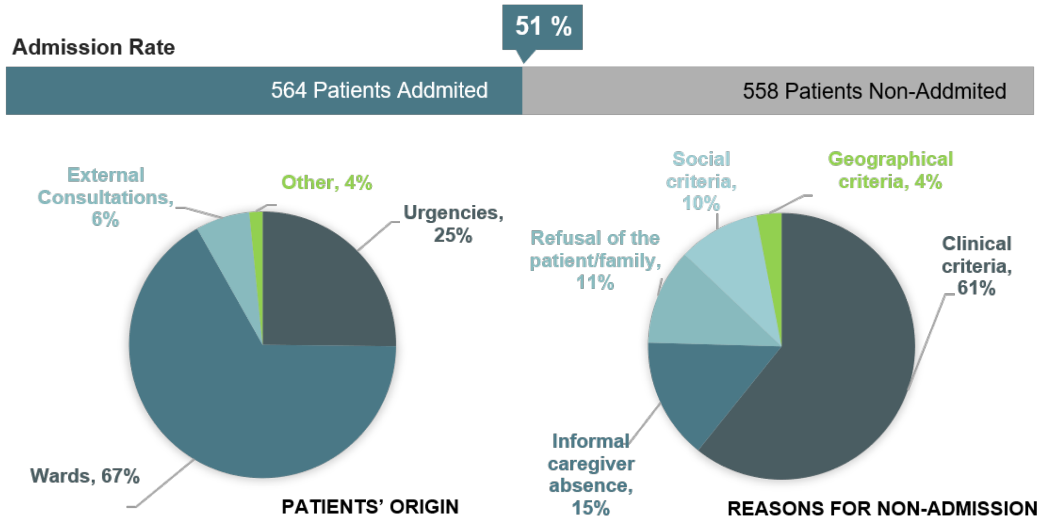

Figure 2.6: Statistics about patients' admission in 2019 (HGO, 2019b)

(Figure 2.5, bottom right). Once the patient is admitted in the HHU, the first visit at home occurs within 24 hours and is made by a physician and a nurse. The nurse that visits the patient in the first visit is the nurse responsible for the patient. However, it is not guaranteed that this nurse will proceed with the next visits. Then, in the subsequent visits, the patient can be visited by a nurse or a physician and a nurse. Nevertheless, the first and last visits always require the presence of a physician. During the hospitalization, the physician may request analyses or exams, which require the transportation of the patient to the hospital. Although all patients in the HHU already have a diagnosis when admitted, they may need to be observed by other specialties to understand the evolution of the diseases. In any case, if needed, transport is provided by HGO at no additional cost for the patient.

The HHU uses the *Sclinico* application for the clinical records, therapeutic procedures, and prescriptions, as is used for conventional hospitalizations. During the visits, the physicians record the observations and status of the patient directly in the application. Additionally, every Monday morning, a team meeting occurs to discuss each patient's condition and estimate the remaining time of hospitalization so that the whole team is aware of the patient's condition. The daily operational process of scheduling and routing is discussed in detail in subsection 2.4.3.

The patient's discharge can be based on three factors: clinical discharge, service transfer, or death. The mortality rate in HH was only 0.88% in 2019, while 14% were transferred to another hospital service. The patient transfer may occur, for instance, due to poor housing conditions, the absence of an informal caregiver, or the need to connect to non-invasive ventilation. The clinical discharge, which represents the remaining 85% of the cases, can be with or without the need for continuous care provided by the Primary Care Team (PCT). Hence, if the intensity and the clinical procedures begin to attenuate, the HHU discusses the possibility of transferring the patient to the PCT sphere, facilitating the post-discharge from the HH.

Resources and capacity

The HHU at HGO has a dedicated room within the hospital, three vehicles for home visits, materials for clinical consumption, transport backpacks, and office supplies. The HHU team comprises approximately ten nurses, eight physicians (general practitioners), one social worker, two pharmaceuticals, one nutritionist, one health manager advisor, one administrative secretary, and one psychologist. Nurses are assigned exclusively to the HHU. Physicians share their time among the HHU, urgency, and consultations. The HHU works 24h/day and 7days/per week since a patient can always need a service. The regular visits are made in the morning, between 9h and 14h. Afterward, home visits can still be provided until midnight, and after that, the unit operates on a nursing and medical prevention basis. Patients can contact the unit at any time for doubts or emergencies.

The maximum capacity of the service is restricted to the available resources, namely physicians, nurses and vehicles. The reference is 10 patients for 1 physician, 2 nurses and 1 vehicle (HGO, 2018). For instance, in 2019, the unit capacity was 20.25 patients per month. The unit estimates its monthly capacity by multiplying the number of patients that they can serve in a day by the total number of days in one month. Then, the occupancy rate is calculated by dividing the sum of days of all patients' internment in one month by the monthly capacity. In 2019 the occupancy rate was around 81%.

Outcomes

The unit has a total of 1633 patients served until the end of 2019 (HGO, 2019b). From 2016 to 2019, the number of patients served almost doubled from 301 in 2016 to 579 patients in 2019 (Figure 2.7). Table 2.2 shows the average statistics of the HHU in 2019. Each visit takes on average 40 minutes, and the Travel Time per visit is around 15 minutes. Each patient stays on average 10.58 days on HHU and during that time receives, typically, 11.44 visits, making an average of 1.08 visits per day per patient.

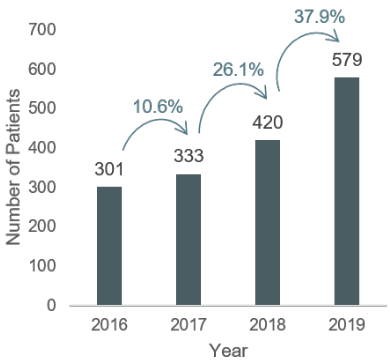

Figure 2.7: Evolution of the number of admitted patients in the HHU (HGO, 2019b)

Average	Travel Time per visit	14.38 min
	Visit duration	39.63 min
	Length of stay	10.58 days
	Number of visits per patient	11.44 visits
	Number of Km per patient	89.54 km

Table 2.2: General statistics of the HHU in 2019 (HGO, 2019b)

The HHU also uses clinical outcomes to evaluate the quality of health care provided. These outcomes are presented in Table 2.3 for 2017-2019. In 2016, the indicators were measured differently, and thus it is not possible to make comparisons (HGO, 2019b).

The HHU has set benchmark values for each of the indicators (column "Desired outcome" in 2.3).

Indicator	Desired outcome	2017	2018	2019
Length of stay	**<10 days**	8.17 days	9.67 days	10.58 days
Transfer rate to hospital	**<10%**	10.12%	9.38%	13.96%
Post-discharge readmission rate (until 30 days)	**<2%**	0%	0%	1.24%
Mortality rate	**<inpatient**	1.23%	1.48%	0.88%
Patient satisfaction index	**>90%**	92%	92%	92%
Family satisfaction index	**>90%**	91%	91%	86%

Table 2.3: Outcomes of the HHU from 2017 to 2019 (HGO, 2019b)

Regarding the length of stay, the desired result was not met in 2019. Nevertheless, compared to the conventional ward, the HHU has significant improvements in this outcome. In 2017, the length of stay in a conventional ward in HGO was 13.6 days, and in the last three years of the HHU activity, the length of stay never exceed this value (HGO, 2019b). Moreover, the unit intends that less than 10% of the admitted patient may need to be transferred to the hospital again, and we can see that this indicator is not being met as well. However, this may occur for reasons such as poor housing conditions or the absence of an informal caregiver. The indicators of post-discharge readmission rate and mortality rate are being met as expected and are showing a significant improvement when compared to the conventional ward of HGO. In 2017, the post-discharge readmission rate until 30 days in the conventional ward was 0.2% while the mortality rate was 12.81%. Thus, the HHU decreased these outcomes to 0% and 1.23%, respectively.

Regardless of these indicators, the HHU also conducts satisfaction surveys to the patient and family. The satisfaction of the patients has been 92%. However, the family members' satisfaction has shown a small decrease in 2019. Nevertheless, the satisfaction surveys allow the unit to identify some key advantages of using HH. Namely, more time exclusively dedicated to the patient, which allows a better assessment of the patient's condition; greater involvement of the patient's family contributing to better health education; and a minor deterioration of the patient's functional status. All these factors also contribute to higher satisfaction of the health professionals since they see their work positively impacting the patient's life.

		2017	2018	2019
Direct costs per discharged patient	HHU	913.65 €	1155.21 €	972.90 €
	Medicine ward	1 686.60 €	1 769.62 €	
Savings per patient (%)		**45.83%**	**34.72%**	
Total Direct costs for 2017 – 326 patients 2018 – 405 patients	HHU	297 849.90 €	467 860.05 €	
	Medicine ward	549 831.60 €	716 696.10 €	
Total savings (€)		**251 981.7 €**	**248 836.05 €**	

Table 2.4: Comparison of direct costs between the HHU and conventional ward per discharged patient

From an economic point of view, this alternative can be economically attractive as well. Table 2.4 shows a cost comparison between HH and a conventional ward per discharged patient. In 2017 the direct cost savings per discharged patient using HH were 45.83% while in 2018, 34.72%. Considering that the discharged patients were respectively 326 and 405, this represents a total saving of approximately 251 981.7€ in 2017 and 248 836.05€ in 2018. The costs reduction is significant, showing the economic potential of the HHU to the hospital.

However, it is important to notice that costs as lighting, hot water, special equipment (e.g., wheelchair, specialized beds), and sometimes transportation to the hospital for exams are transferred to the patients and their families.

2.4.3 Scheduling and Routing Decisions

The paradigm shift in care requires an organization that is structurally different from conventional hospitalization. Thus, some logistical issues that were not previously considered need now to be well-thought-out: creating teams and assigning teams to patients' visits; defining routes for each team; measurements of performance and efficiency. One significant challenge faced by the HHU regards the scheduling and routing decisions.

Patients in HH need to be visited every day as they were at the hospital. Depending on the physicians' availability and the care required, these visits can be done by a team of one nurse and one physician or a single nurse. The number of physicians available is only known on the day itself. Therefore, all staff members gather at a morning meeting in the hospital due to last-minute changes. There are currently three vehicles available for visit and, thus, three teams. In the first stage, patients are divided into three groups considering only their addresses. Then, each group of patients is randomly allocated to a nurse. The allocation of physicians to teams depends on the number of physicians available. For instance, if there is only one physician, (s)he will be allocated to the group with a higher number of patients in a more aggravated state. However, if there are three physicians available, one for each team, the allocation of physicians to the groups of patients is done randomly.

After assigning teams to patients, the routing decisions are decided by each team. Thus, each nurse defines the route considering three main aspects: distances, local traffic, and patient status. The latter needs to be considered when, for instance, a patient needs to take an antibiotic in the early morning. Thus, if there is a patient in this situation, this patient is the first to visit. Then, the remaining route is made according to distances and local traffic. After planning the routes, nurses prepare their backpacks with the necessary material to perform all the visits. Additionally, they take with them paper files where all the nursing interventions and the patient's conditions are recorded, for example, body temperature and blood pressure. The physicians have a computer where they can remotely access all the clinical history of the patients.

Overall, this manual planning is time-consuming, often requiring around 30-45 minutes every morning, thus delaying the teams' departure. Moreover, all these decisions are based on health care professionals' experience with no systematic or decision support.

2.5 Problem Definition

HH has been a topic of growing importance in recent times in Portugal. Although some progress has already been made, there are still areas requiring further development, namely logistics and operations planning.

In meetings conducted with the HHU, including a day accompanying one team during the patient's visits, it was possible to understand and identify the main challenges faced by the unit. Firstly, the fact that the whole process is currently done manually, requiring a long time to obtain a valid schedule that respects all the constraints. Moreover, it relies on the nurses' memory and experience regarding the patients' addresses, making it even more complicated when a new patient is introduced. Another aspect regards the Workload Balance in team management. The head nurse of the unit refers to the importance of having the work well distributed between teams so that there are no feelings of injustice, discouragement, and above all, to promote a good atmosphere in the unit. Lastly, the unit would like to incorporate other aspects to improve the service's quality, such as Continuity of Care, i.e., having the same team always visiting the same patient. Since patients are visited in their homes in HH, they would rather prefer to see a familiar face instead of a different face every day. Additionally, if the care worker visits the same patient every day, knows better the patient's history from the past visits, and can provide the service more effectively without going through the patient's records or asking more questions. Similarly, continuity within the nurse-physician teams should also be studied. However, as physicians also work in other hospital departments, it is challenging to consider this aspect.

This dissertation aims to develop a method to support the scheduling and routing decisions of an HHU, with HGO as the main case study. The objective is to deliver a daily schedule and route for each team, to provide the planned care visits, respecting some constraints. The schedule should indicate the patients that each team has to visit (corresponding to a location), the visiting start time, and the visits' order. The method must balance Travel Time with Continuity of Care while ensuring Workload Balance. Patients needing first-visits and allocate the patients in an aggravating condition to teams with physicians should also be considered. Since this planning is performed every day and often requires much time, there is an essential axis of improvement to grow the HHU.

2.6 Chapter conclusions

The aging population has led to an increasing demand for hospital beds. Consequently, recent health care services have emerged as a response to this problem, which is the case of HHC and HH. Although the statistical evidence in OECD countries shows that HHC services are growing sector in health care, it is not possible to make the same conclusion about HH. The reason for this may be due to the different definitions of the concepts by the various countries, originating different forms of measurement in the statistics. Nonetheless, HH emerges as an alternative to conventional hospitalization, concerning patients who would be in a hospital in the absence of this service. Thus, providing hospital care that is not provided in HHC services.

Portugal has a significant aged population and has seen in HH an opportunity to decrease hospital congestion. Encouraged by the government to adapt the health care system to the growing needs of an aging population, HH has been expanding rapidly over the last few years. HGO was the first hospital to implement an HHU in Portugal and has already confirmed the benefits of the unit. Compared to the conventional ward, the HHU has significant improvements in costs, length of stay, mortality rate, and post-discharge readmission rate. The HGO believes in the innovative character of this patient-centered response and intends to continue to grow the number of patients served and, above all, to improve the quality of service.

Nevertheless, this service brings complex logistics decisions that need to be considered and are currently being done manually. For this reason, the goal of this dissertation is to develop a method to support scheduling and routing decisions of the HHU, taking into account the problems pointed out by the unit.

Chapter 3

Literature Review

This chapter provides an overview of the existing literature regarding planning decisions in HHC since the literature in HH is scarce. Although the case under study focuses exclusively in HH, a review in planning decisions and literature in HHC is provided since, in terms of operations and logistics planning, the decisions are roughly the same (section 3.1). Then, focusing on the operational decisions staff assignment, scheduling, and routing, an overview of the different constraints, objectives, and solutions methodologies already studied in the literature is presented (section 3.2). Finally, section 3.3 presents the chapter's conclusions and possible future works.

3.1 Planning Decisions in Home Health Care organizations

HHC services are showing a significant growth mainly because it is, in general, less costly and impacts patients' quality of life positively. Nevertheless, this type of service implies integrating and coordinating several factors, such as a new step in the supply chain (i.e. the patients' home), patients' preferences, and travel costs. To provide high-quality care at the least cost possible, complex logistics and operations decisions need to be considered making it an interesting problem to apply Operations Research techniques.

Frameworks to classify planning decisions in the field of HHC are proposed in the literature (Cissé et al., 2017; Gutiérrez, 2014; Hulshof et al., 2012; Matta et al., 2014). Figure 3.1 shows the breakdown of strategic (subsection 3.1.1), tactical (subsection 3.1.2) and operational planning (subsection 3.1.3) for HHC based on the reviewed articles.

3.1.1 Strategic Planning

Strategic planning considers a time horizon of more than one year and includes decisions to support long-term objectives. Firstly, the HHC organization needs to establish its placement policy by defining a classification system to assess which patients are eligible for HHC services. Then, the regional coverage decision is related to the number, location, and type of HHC facilities in each region. Lastly, the service mix consists of deciding the types of services to deliver. These three decisions define the mission and strategy of the HHC organization (Hulshof et al., 2012).

Regarding the districting decision, it consists of the partitioning of each HHC service territory into suitable districts (or clusters of patients), based on demography or geographical characteristics. This decision helps decrease travel distances and Travel Times of care workers and encourages the same care workers to serve the same patients, contributing to a long-term relationship (Gutiérrez, 2014).

The last strategic decision to consider is the capacity planning regarding staff levels (i.e., nurses, social workers, physicians) – the number of staff depends on their skills and working preferences, equipment, and fleet vehicles. The problem should consider the number of resources needed depending on the estimated patients' demand and needs (Matta et al., 2014).

3.1.2 Tactical Planning

The tactical level involves intermediate decisions made for often between six months and one year and usually implements the strategic decisions. The capacity planned at a strategic level (i.e., staff, equipment, vehicles) is assigned to each district – capacity allocation. Even though the patients are qualified for HHC services through the placement policy, the rules from which patients are chosen from the waiting list also compose a decision - admission control (Hulshof et al., 2012).

Shift scheduling is a decision that selects the shifts' time specifications and assigns a specific number of employees to each shift. To respond to unexpected increases in demand, some HHC organizations employ temporary staff during specific shifts - staff allocation (Gutiérrez, 2014).

3.1.3 Operational Planning

Finally, the operational planning related to short term decisions concerns the coordination of activities, including offline and online decisions. Offline decisions are taken in advance while online reflects real-time reactive decision-making, depending on unpredicted events (Hulshof et al., 2012).

At the offline level, decisions such as assessment and intake consist of deciding to admit a specific patient in the service, based on the previously defined placement policy and the patient's social and psychological conditions. Then, determining the type of care to deliver to each patient and the number of visits needed per day or week. This care plan needs to be customized to each patient since the patient's conditions are particular (Hulshof et al., 2012). The staff-to-shift assignment decision deals with allocating care workers to shifts over time, depending on the shift scheduling decision defined at the tactical level and on constraints such as working regulation and employee preferences. Then, the last three decisions: staff-to-patient assignment, scheduling, and staff routing, have been addressed in different ways in the literature. On the one hand, some authors consider in the first stage only the staff-to-patient assignment decision. In this way, a patient is going to be visited by one and only one care worker during the planning period. After, the planning for the scheduling and routing is done. On the other hand, other authors consider the three decisions simultaneously since they are highly interdependent. Instead of assigning staff to patients, a staff-to-visit assignment is performed, which assigns patients' visits to care workers. The scheduling decision then gives the day and time that each visit will be performed and the care worker responsible for that visit. Finally, the staff routing consists of the sequence of visits that each care worker needs to perform during the planning period (Gutiérrez, 2014; Hulshof et al., 2012;

Lanzarone, Matta, 2014; Matta et al., 2014).

At an online level, which can be short notice or in the day itself, managing unplanned activities is the main decision at stake: if a patient needs to be visited due to an emergency or an unplanned care worker absenteeism is going to affect the schedule and implies a modification of routes. Real-time information about care workers' routes would help in redefining the schedule (Matta et al., 2014). Online decisions have not been incorporated in most of the studies. Most of the authors deal with static scheduling, which does not reflect the real-life changing of events. Other authors are already considering the uncertainty regarding patients' demand and Travel Times based on historical data to build more robust models. However, real-time scheduling has not been addressed much in the literature. Only Du et al. (2019) considered the impact of unexpected events – the cancellation of the service and urgent patients added; and proposed a real-time scheduling problem by readjusting the initial plan, based on the actual need of patients. The performance measures were response time and patients' satisfaction. However, in this case, each patient could only receive one medical service per week.

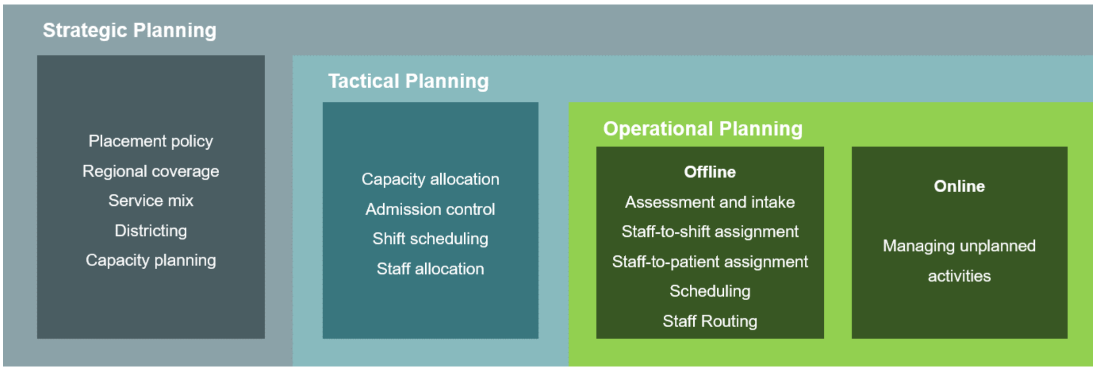

Figure 3.1: Planning Decisions in HHC

3.2 Home Health Care Routing and Scheduling Problem

This paper focuses on the offline operational decisions related to the staff-to-patient assignment, scheduling and staff routing. As explained before, existing literature on HHC can be divided into two parts (Marcon et al., 2017; Yalçındağ et al., 2016a). Firstly, the authors who consider a two-stage approach, assigning first patients to care workers (first stage) and then scheduling and routing decisions are considered (second stage) – two-stage method. Then, the authors who consider a more flexible approach, studying the three decisions simultaneously - the single-phase method.

Regarding the two-stage approach, there are some studies only about the first stage – staff-to-patient assignment; either focusing on the Continuity of Care (Lanzarone, Matta, 2014) or considering the effect of Travel Times (Yalçındağ et al., 2016b). Yalçındağ et al. (2016a) studied the two stages in a sequence, using the output from the first stage (i.e., the set of patients assigned to each care worker) as an input for the second stage. Moreover, the authors compared this approach with the single-phase one and concluded that there is a trade-off between flexibility and dimension of instances since a two-stage approach can fail in providing feasible solutions, while a single-phase method may afford only small instances.

Nevertheless, most of the studied authors address the three decisions simultaneously. Most of the works refer to this problem as the Home Health Care Routing and Scheduling Problem (HHCRSP) (Cissé et al., 2017), however, there is no single denomination for this type of problems, having received several different names in the literature: Home Health Nurse Routing and Scheduling (Bennett, Erera, 2011), Home Care Crew Scheduling Problem (Rasmussen et al., 2012), Home Care Planning Problem (Maya Duque et al., 2015), Home Care Worker Scheduling and Routing Problem (Liu et al., 2017), Home Healthcare Nurse Scheduling Problem (Demirbilek et al., 2019). Despite the different names emerging in the literature, the general idea of all these problems consists of finding a schedule and route for each care worker to provide the planned care visits over a planning horizon, respecting some constraints. The resulting planning must indicate which visit must be performed by which care worker, in which order, and at what time. It is essential to establish the planning period – a single day, an entire week, or many months; in which those decisions are going to be made. Most of the articles deal with a single day-planning; however, some papers consider a longer horizon (Grenouilleau et al., 2019; Maya Duque et al., 2015; Yalçındağ et al., 2016a). In Single-period HHC problems, the number of staff is often fixed, while in Multi-period, nurses may work multiple days, and clients may request multiple services spread over different days of a week or month. Thus, a longer planning horizon requires a more challenged and sophisticated use of constraints (Fikar, Hirsch, 2017).

Apart from that, some literature reviews already highlight the most relevant features, constraints, and objectives used by the different papers and other relevant sources (Cissé et al., 2017; Di Mascolo et al., 2017; Fikar, Hirsch, 2017). Most of the reviewed articles considering assignment and routing problems solved jointly deal with the HHCRSP as an extension of the combinatorial optimization Vehicle Routing Problem (VRP) or Vehicle Routing Problem with Time Windows (VRPTW), augmented by new constraints that are specific to the HHC problem (Akjiratikarl et al., 2007; Bredström, Rönnqvist, 2008). The goal of the VRP is to find the best routes (e.g., routes with the least cost or distance) for multiple vehicles visiting a set of locations and return to the starting point. VRPTW is a specific case of the VRP in which the costumers must be visited in specific time intervals.

The main differences within the papers are the considered objectives, the different constraints used, and the solution methodologies applied. In HHC case studies, there are no identical conditions, and the patient is in the center of the decision-making system. Consequently, there are no standard objectives and constraints used in all types of problems (Cissé et al., 2017). The remaining literature review concentrates on the main aspects in HHCRSP problems: main characteristics and features considered while modeling the problem (subsection 3.2.1), objective functions or performance measurement (subsection 3.2.2) and solution methodologies (subsection 3.2.3). At the end of each section, a summary table is presented with some of the papers divided into Single-Period – daily planning; and Multi-Period – more than one day.

3.2.1 Main Characteristics

Even though the features used in the different articles do not seem to change substantially, the way they are implemented differs (Fikar, Hirsch, 2017). Each feature can be formulated as a constraint or as a satisfaction criterion in the objective function (Cissé et al., 2017). The different features are divided into four different categories – temporal, assignment, geographic, and uncertainty-based features.

Temporal-based Features

Some authors define a visit pattern for each patient, which indicates the time slots for the patient to be served, depending on the patient's care profile (e.g., if a patient needs three visits per week, a possible pattern can be Monday-Wednesday-Friday) (Yalçındağ et al., 2016a). Some care profiles require a minimum number of visits or a time lag between visits (Maya Duque et al., 2015). Considering this, some authors also consider the periodicity or consistency of the services, which means that a set of services for a given patient should occur on the same day and time on each week, during the planning horizon, applying a visit-time consistency constraint (Bennett, Erera, 2011; Demirbilek et al., 2019; Maya Duque et al., 2015).

Regarding time windows, some articles consider hard time windows – the service needs to start and finish inside of the specified time window (e.g., if care workers arrive before the start of the time window, they have to wait) (Braekers et al., 2016) while other publications consider soft time windows allowing for flexibility. However, if a service is performed outside of the soft time windows, a penalty is added to the objective function (Bertels, Fahle, 2006). This feature is essential because most of the tasks in HHC are time-sensitive (e.g., insulin injection) (Fikar, Hirsch, 2017). Moreover, it is also possible to add preferred working time windows for each nurse to specify the care workers' preferences regarding the schedule (Maya Duque et al., 2015). Again, if not respected, a penalization is added in the objective function. Additionally, patients can also have preferences for visiting times (Maya Duque et al., 2015; Trautsamwieser, Hirsch, 2014).

The type of contract (e.g., full or half time, externally subcontracted) also impacts the problem (Trautsamwieser, Hirsch, 2011). The costs and constraints regarding each contract are necessarily different. In addition, overtime work is also a used feature when the care workers need to work more than the regular time and additional compensation for the overtime hours is paid (Grenouilleau et al., 2019). When overtime is possible, soft time windows are used, and overtime is penalized in the objective function. Cheng, Rich (1998) addressed this problem with both full-time and part-time nurses, and their objective minimizes overtime and part-time work schedule since part-time nurses are paid per hour. Nevertheless, when overtime is not allowed, hard time windows are used.

Working limits (daily or weekly) can also be applied to respect the working time regulations. The limit is going to depend on the country and concerns legal provisions. The respect of the working limits can be done either by setting working time windows, a maximum total distance, or total working time (Braekers et al., 2016). Here, overtime can also be allowed, yet, each additional unit is penalized with a higher cost in the objective function. Nonetheless, the total working time limit cannot be exceeded (Nickel et al., 2012). Finally, unavailability of care workers should also be considered due to holidays, days off, or sick leaves (Trautsamwieser, Hirsch, 2014), even though few papers deal with these features.

In some cases, care workers' breaks are also considered (Liu et al., 2017). The break can happen within a specific period or when a determined route length is reached by setting a cumulative working time. Trautsamwieser, Hirsch (2014) created an additional decision variable - the starting time of the break; to model it and assume that breaks are taken at the patients' houses. Otherwise, a break can be represented by a fictitious patient who has to be visited by each care worker.

Interdependent services have also been studied in the literature (see, for example, Bredström, Rönnqvist, 2008; Mankowska et al., 2014). This means that one service should be planned a specific time after or before another service (e.g., provide medication after lunch). Moreover, it is possible to have disjunctive services - services that cannot be provided at the same time to a patient (e.g., blood collection and physical therapy); or, oppositely, synchronized services (e.g., lift heavy patients) (Yuan et al., 2015). Since in synchronized services, the time that both care workers are needed can be only a few seconds, Decerle et al. (2018) extended the concept of soft time windows to synchronization constraints. Thus, a penalty function whose value depends on the gap between the arrival time of both vehicles is used, bringing more flexibility to the model.

Assignment-based Features

As said before, the increasing concern regarding the quality of the service led to the appearing of other features in HHC optimization such as matching care workers' qualifications/skills and patients' needs. These qualifications may be related to the type of care worker (e.g., physician, nurse, nutritionist) or the care worker specialty (e.g., medical-surgical, rehabilitation). These types of constraints are often modeled by attributing qualification levels to care workers and services. A care worker is only allowed to visit a patient if the qualification level is higher or equal than the service required from a patient (Braekers et al., 2016; Grenouilleau et al., 2019; Trautsamwieser, Hirsch, 2014). Patients preferences regarding the care worker, such as language, gender, among others, also generate assignment constraints (Lanzarone, Matta, 2014; Martin et al., 2020).

The notion of Continuity of Care related to the patient and care worker consistency is starting to become a trending feature in HHC problems (see, for example, Wirnitzer et al., 2016). The reason so is because, in this way, there is no loss of information among care workers, and it reinforces the relationship between the patient and the respective care worker. Some models consider Continuity of Care as a hard constraint which implies that a patient is always visited by one and only one care worker - full Continuity of Care; or by a limited group - partial Continuity of Care; over the planning horizon (Cappanera, Scutellà, 2015; Yalçındağ et al., 2016a). Thus, a care worker can visit a patient only if (s)he has been assigned to that patient. However, it is difficult to keep this constraint while respecting other temporal and assignment constraints, moreover, when the patients can be visited more than once per day. For this reason, other models consider Continuity of Care in the objective function as a soft constraint. Thus, they focus on keeping the number of care workers assigned to each patient at the minimum level (Lanzarone, Matta, 2014; Nickel et al., 2012). Similarly, Grenouilleau et al. (2019) use a score for Continuity of Care based on the number of times a care worker has been assigned to a patient. The score appears in the objective function as a cost that needs to be minimized.

Finally, Workload Balance can also be considered an assignment constraint to guarantee work equity within care workers and keep them motivated (Braekers et al., 2016). Typically, this feature is considered in the objective function by minimizing the maximum working time difference within care workers (Decerle et al., 2019a).

Geographic-based Features

Some papers consider a single start and finish location of care workers (i.e., a depot in VRP). However, the case of multi-depots has already been considered, using more than one HHC center or even considering that nurses can start and finish the visits from their houses (Trautsamwieser, Hirsch, 2011). Even though most of the papers assume a single transport mode, care workers may also use various transport modes (Eveborn et al., 2006). Furthermore, Quintanilla et al. (2020) study the case where care workers travel by taxi, meaning that traveling and waiting costs of the employed taxis have to be considered.

Uncertainty-based Features

We observe that almost all the papers deal with static problems, considering that everything is known in advance and no uncertainty in demands or service times is considered. However, the patients' inconstant health conditions and other possible random events make the service demand highly uncertain. Recently, stochastic settings started to appear in the literature, aiming to estimate demand (Shi et al., 2017), travel (Shi et al., 2018) and service times (Bennett, Erera, 2011). Lanzarone, Matta (2014) consider the stochasticity of new patients' demand and nurses' workloads. The model shows significant results regarding the objectives considered (i.e., lower overtime and better Workload Balance) for cases where the patients' demand has high variability. In situations characterized by low demand variability (e.g., palliative patients), these results are not that significant.

Apart from that, some articles consider dynamic aspects, where patients and information regarding their futures requests are revealed dynamically and are not known in advance. Demirbilek et al. (2019) consider a dynamic problem with acceptance and scheduling as soon as a patient arrives, without waiting until the next schedule period and anticipating future demand. However, the paper deals with the unrealistic and straightforward case of a single care worker.

Time-dependent Travel Times have also been studied since there can be rush hours or off-peak times, meaning that Travel Times can change significantly. Grenouilleau et al. (2019) consider the impact of traffic on Travel Time through a time-dependent distance matrix. Additionally, Yalçındağ et al. (2016b), based on historical data of patients' geographical locations (i.e., traffic conditions and accessibility of patients' homes) computed travel estimations to improve nurses' assignments. Yuan et al. (2018) uses a discrete approximation method to calculate the arrival time distribution of care workers at patients locations, assuming that the probability distributions for travel and serve times are known.

Risk management in HHC regarding potential natural disaster was studied by Rest et al. (2012). The paper investigates exemplary how potential floods can impact HHC services. The authors also explore the impact of the type of network (i.e., rural or metropolitan) since travel duration is likely to be different.

Table 3.1 summarizes the main features used in the literature. The table shows some features that are almost always considered by the different authors, such as time windows to structure the problem (soft or hard), care workers' qualifications, and working time regulations. Later, papers incorporating patients' preferences and interdependent services started to appear. Features such as consistency/periodicity, Continuity of Care, and dynamic aspects are more common in Multi-period problems since those decisions have a more prolonged impact than one day. Stochastic settings are also starting to emerge, yet only a few articles consider this feature.

Article	TW	C/P	WL	B	IS	CQ	PP	CC	D	S
Single-Period										
Akjiratikarl et al. (2007)	X		X							
Bertels and Fahle (2006)	X		X	X		X	X			
Braekers et al. (2016)	X		X			X	X			
Bredström & Rönnqvist (2008)	X		X		X	X	X			
Decerle et al. (2018)	X		X		X	X				
Decerle et al. (2019)	X		X		X	X				
Eveborn et al. (2006)	X			X	X	X	X	X		
Liu et al. (2017)	X		X	X		X		X		
Mankowska et al. (2014)	X		X		X	X				
Rasmussen et al. (2012)	X				X					
Trautsamwieser and Hirsch (2011)	X		X	X		X	X			
Yuan et al. (2015)	X		X			X				X
Multi-Period										
Bennett et al. (2011)	X	X	X						X	
Cappanera & Scutellà (2015)	X	X	X			X		X		
Demirbilek et al. (2019)	X	X							X	
Du et al. (2019)	X					X			X	
Grenouilleau et al. (2019)	X		X			X	X	X		
Martin et al. (2020)	X		X			X		X		
Maya Duque et al. (2015)	X	X	X			X	X	X		
Nickel et al. (2012)	X		X	X		X		X		
Trautsamwieser and Hirsch (2014)	X		X	X						
Total (21)	**21**	**4**	**17**	**6**	**6**	**16**	**7**	**7**	**3**	**2**

TW, Time Windows; C/P, Consistency/Periodicity; WL, Working Limits; B, Breaks; IS, Interdependent Services; CQ, Care workers Qualifications; PP, Patients Preferences; CC, Continuity of Care; D, Dynamic Aspects; S, Stochastic Settings

Table 3.1: Characteristics considered in related work of HHCRSP

3.2.2 Objective Functions

Most of the articles from early literature use an extension of the combinatorial optimization VRP or VRPTW where travel is the primary concern (Akjiratikarl et al., 2007; Rasmussen et al., 2012). For this reason, HHC problems often consider the minimization of Travel Time, travel cost, or travel distance.

Additionally, as care workers' working times are the main cost factors, overtime and working time are often considered as well. Concerning care workers' satisfaction, one criterion which usually is considered in objective functions is the Workload Balance, either by counting the number of services assigned to each care worker or the working time (Cappanera, Scutellà, 2015). Some authors also try to minimize the number of workers starting a route since it can significantly reduce staff costs (Martin et al., 2020). Additionally, some authors opt to maximize the number of patients' visits during the planning horizon or minimize uncovered visits (Bennett, Erera, 2011; Demirbilek et al., 2019).

Nevertheless, some works are already starting to consider aspects that increase the quality of the service to match real situations such as Continuity of Care, skill assignments, and the non-satisfaction of the soft time windows, through constraints violations. Many authors use weighted objective functions to account for both - costs and patient satisfaction - integrating all objectives into one function to work on a single objective optimization framework. Trautsamwieser, Hirsch (2011) use a weighted objective function which minimizes Travel Times and waiting times of nurses and, at the same time, maximizes the satisfaction of both clients (i.e., preferred nurses and treatment times) and nurses (i.e., overtime, overqualification, preferred working times and breaks). In this case, the weights were chosen by the respective decision-makers.

By contrast, multi-objective functions are not so commonly used in HHC scheduling and routing, even though HHC organizations are often confronted with conflicting objectives. However, to study the trade-off between costs and patients' preferences, Braekers et al. (2016) consider the two possibly conflicting objectives and developed a bi-objective problem, accounting for several constraints - qualifications, working regulations, overtime, among others. Thus, multiple solutions are obtained, and the decision-makers can investigate the possible trade-offs. Results show that the average service level may improve drastically with a relatively small penalization on the costs. Similarly, Maya Duque et al. (2015) developed a bi-objective mathematical problem that aims to maximize service level and minimize the travel distance. A two-stage approach is used, maximizing first the service level - considered by the author as the main criterion -, and then minimize the total traveled distance while allowing a certain fixed decrease of service level. Recently, Martin et al. (2020) also propose a bi-objective problem to minimize the number of care workers and, simultaneously, the total required time to visit all patients.

Carello et al. (2018) study the trade-off between the interests of the different stakeholders involved: patients – the quality of service; care workers – fair workloads; and managers – low costs. The three perspectives are modeled as alternative objective functions, and a threshold method is used to include all of them. Results show that the quality of the service and fair workloads can be achieved with a limited cost increase — however, the paper focus only on the staff-to-patient assignment decision. Even though most of the authors opt to work on a single objective environment rather than in a multi-objective one (i.e., weighted functions rather than multi-objective functions), it is crucial to notice that asking the decision-makers a priori to assign appropriate weights to different terms in the objective function can be a difficult task. Moreover, a multi-objective approach finds different efficient solutions instead of a single optimum, giving more information for decision-making (Fikar, Hirsch, 2017).

The main objectives used in the reviewed literature are summarized in Table 3.2. For simplification, the objectives Travel Time, travel distance, and travel cost are all considered in the first objective named Travel (T) in the table. The last four columns represent soft constraint violations, which are penalized in the objective function.

Article		T	WT	OT	WB	U	NC	SC PP	SC CC	SC TW	SC IS
Single-Period											
Akjiratikarl et al. (2007)	SO	X									
Bertels and Fahle (2006)	WS	X	X					X		X	
Braekers et al. (2016)	MO	X		X				X		X	
Bredström & Rönnqvist (2008)	WS	X			X			X			
Decerle et al. (2018)	SO	X								X	X
Decerle et al. (2019)	SO	X			X						X
Eveborn et al. (2006)	WS	X						X	X		
Liu et al. (2017)	SO	X				X					
Mankowska et al. (2014)	WS	X			X					X	
Rasmussen et al. (2012)	WS	X				X		X			
Trautsamwieser and Hirsch (2011)	WS	X		X				X		X	
Yuan et al. (2015)	SO	X	X				X			X	
Multi-Period											
Bennett et al. (2011)	SO					X					
Cappanera & Scutellà (2015)	SO				X						
Demirbilek et al. (2019)	SO					X					
Du et al. (2019)	WS	X	X					X			
Grenouilleau et al. (2019)	WS	X		X		X		X	X		
Martin et al. (2020)	MO	X	X				X				
Maya Duque et al. (2015)	MO	X						X			
Nickel et al. (2012)	WS	X		X		X			X		
Trautsamwieser and Hirsch (2014)	SO		X								
Total (21)	**SO (9) | WS (9) | MO (3)**	**17**	**5**	**4**	**4**	**6**	**2**	**9**	**3**	**6**	**2**

SO, Single Objective; WS, Weighted Sum; MO, Multiple Objective; T, Travel; WT, Working Time; OT, Overtime; WB, Workload Balance; U, Unscheduled Tasks; NC, Number of Care workers; SC, Soft Constraints; PP, Patients Preferences; CC, Continuity of Care; TW, Time Windows; IS, Interdependent Services.

Table 3.2: Common Objectives and Performance Measures in HHCRSP

3.2.3 Solutions methodologies

To solve the problems, the literature develops exact, metaheuristics, and hybrid solutions. Regarding exact methods, most papers dealing with the single-planning horizon use Branch-and-Price (B&P) algorithms. Rasmussen et al. (2012) modeled the problem as a Set Partitioning Problem (SPP) accounting for five types of temporal dependencies and developed a B&P framework to solve the problem. Yuan et al. (2015) use a B&P algorithm and devise a labeling algorithm to solve the pricing sub-problem optimally, incorporating stochastic service times and multi-type care workers. Liu et al. (2017) use a similar method but accounting for lunch break requirements.

However, due to the complexity of the problems, there are already a diversity of approximate methods. Eveborn et al. (2006) presents a decision support system called “LAPS CARE” with several components - databases, map data, optimization routes, and flexible Gantt-charts to show solutions. The model was formulated as an SPP and solved heuristically by using a repeated matching algorithm. The system allowed a reduction in 7% of the total working time and 20% in Travel Time. Akjiratikarl et al. (2007), which modeled the problem as an extension of the VRPTW, use a population-based metaheuristic algorithm called Particle Swarm Optimization (PSO). This technique explores the solution space globally and uses local improvement procedures to refine the search in the neighborhood area. For the daily planning of HHC services, Trautsamwieser, Hirsch (2011) apply the Variable Neighborhood Search (VNS), solving real-life instances with up to 75 nurses and 420 patients. In order to solve larger instances, Mankowska et al. (2014) propose a metaheuristics procedure using an adaptive VNS algorithm, which adapts the sequence in which VNS searches neighborhoods according to the problem instances. This procedure can solve instances with 30 care workers and 300 patients.

More recently and considering a longer planning horizon, Martin et al. (2020) proposed a version of the metaheuristics method Ant Colony Optimization (ACO) with modifications in the representation of the problem and with additional mechanisms to deal with constraints such as Continuity of Care. This technique improved previous instances in terms of costs and helps at the same time in decision-making between competing objectives - total time for the contracts and number of care workers – since it finds a full range of feasible and efficient solutions. The algorithm was tested with a very large real-world instance of 10,709 patients. To deal with stochastics Travel Time and service time, Shi et al. (2018) propose a stochastic programming model with recourse and solve it by integrating the stochastic simulation method and a Simulated Annealing (SA)-based heuristic algorithm. By comparing to the SPP model reduced to a determinist one, experiments show that the robustness of considering stochastic travel and service times results in less total costs and lower service time delays.

Some authors are using hybrid approaches to take advantage of both exact solutions and metaheuristics. In a single-planning period, considering time windows and qualifications, Bertels, Fahle (2006) use a two-phase approach which first finds a partition of jobs to care workers with Constraint Programming (CP) and secondly, an optimal sequencing for each care worker is designed with the help of linear programming. Then, either Tabu Search (TS) or SA are used to improve the solution being the combination of CP and TS, the one that brings better results in the tested instances. To solve the bi-objective problem, Braekers et al. (2016) propose a multi-objective mixed-integer linear programming model and firstly solved it using the ϵ - constraint solution framework. Then, for larger instances, the authors developed a metaheuristics solution approach, embedding a large neighborhood search heuristic in a multi-directional local search framework to find a set of Pareto optimal solutions. More recently, Decerle et al. (2019b) developed a Memetic Algorithm (MA) as the hybridization of a genetic algorithm with a local search procedure to solve a problem with time windows and synchronization. Later, a hybrid algorithm which combines MA and ACO was introduced by the same author to deal with working time balance (Decerle et al., 2019a). Experiments using benchmark instances suggested by Bredström, Rönnqvist (2008) show a good efficiency of this method when compared with other methods.

Regarding multi-planning period, Nickel et al. (2012) use a two-sage approach generating first a medium-term master plan using CP technique and then, solving an operational planning problem to generate weekly plans, with an adaptive Large Neighborhood Search (LNS). Grenouilleau et al. (2019) present a Set Partitioning Heuristic (SPH) where a set partitioning formulation is solved using the columns generated by an LNS framework, and then a constructive heuristic is called to build an integer solution. This method is able to account for several constraints and provide an average reduction on the Travel Time of 37% and an increase in Continuity of Care of 16% when compared to real-world instances from a home health care agency.

Article	E	H/M	HB	Method	IT	NC	NP	A
Single-Period								
Akjiratikarl et al. (2007)	X	X		PSO with local improvements	R	12	50	
Bertels and Fahle (2006)		X		CP with TB and SA	G	50	200	
Braekers et al. (2016)			X	LNS	R	89	182	+
Bredström & Rönnqvist (2008)		X		Heuristics	G	16	80	+
Decerle et al. (2018)			X	MA	L[1]/R		103	+
Decerle et al. (2019)			X	MA and ACO	L[1]	16	80	
Eveborn et al. (2006)		X		Repeated Matching	R	20	123	
Liu et al. (2017)	X			B&P	L[2]/R	12	100	
Mankowska et al. (2014)		X		AVNS and Local Search	R	40	300	
Rasmussen et al. (2012)	X			B&P	L[1]/R	15	150	
Trautsamwieser and Hirsch (2011)		X		VNS	R	75	411	
Yuan et al. (2015)	X			B&P	L[2]		50	
Multi-Period								
Bennett et al. (2011)		X		Heuristics (Capacity and Distance)				
Cappanera & Scutellà (2015)	X			Integer Linear Programming	R	11	163	
Demirbilek et al. (2019)		X		Scenario-Based Approach				
Du et al. (2019)			X	MA + LS	G	5	80	
Grenouilleau et al. (2019)			X	SPH + LNS	R/RG	20	150	+
Martin et al. (2020)		X		ACO	R		10709	
Maya Duque et al. (2015)		X		MIP and local search	R	21	109	
Nickel et al. (2012)			X	CP, TS and Adaptative LNS	R	12	95	
Trautsamwieser and Hirsch (2014)			X	B&P&C and VNS-based	R	9	45	

E, Exact; H/M, Heuristic/Metaheuristics; HB, Hybrid; IT, Instance Type; R, Real; RG, Randomly Generated; L, Literature; NC; Number of Care Workers; NP; Number of Patients; A, Instances Available

[1] Bredström & Rönnqvist (2008)

[2] modified from the classical Solomon's VRPTW benchmarks (Solomon, 1987)

Table 3.3: Solution Methodologies and Instances used in HHCRSP

Table 3.3 shows the solution methodologies adopted by the different studied authors and the respective instances solved with those solutions. The instances (IT) used are classified as real (R), randomly generated (G), and literature (L). The literature instances, when used, are usually adapted for the specific case of the paper. Two papers were mentioned as a reference for literature instances: Bredström, Rönnqvist (2008) and Solomon (1987). Nevertheless, most of the time, instances are either from the real case understudy or randomly generated. Thus, there are no available instances that are used for benchmark analysis. Columns NC and NP represent, respectively, the maximum number of care workers and the maximum number of patients used on the computational tests. Some papers do not specify this information, so a blank space is left. The last column indicates if the instances used are publicly available.

3.3 Chapter Conclusions

The literature review shows that the most common constraints used in the HHCRSP are time windows, working time regulations, and skill requirements. However, some aspects pointed out as possible future researches in past articles are already starting to appear. For example, Continuity of Care and time dependencies aspects have been receiving a higher focus lately. Moreover, increasing the robustness of the models accounting for stochastic settings and considering dynamic acceptances due to real-life aspects have been studied as well. However, in general, most of the papers address the problem in a static and deterministic context, not accounting for uncertainty related to Travel Time or variability of care duration. Another gap in the literature related to uncertainties is the absence of mechanisms that handle online decisions and react to unforeseen circumstances. Planners are always faced with last-minute changes due to care workers or patients - emergencies can occur, and patients may need to cancel visits, or nurses may be sudden unavailable. Future research should be pursued to account for this uncertainty and propose models that readjust initial schedules at a real-time level for the remains of the planning period.

Even though there are many papers concerned with patients and care workers' preferences regarding skills and visiting times, aligning the patients' care requirements with the visiting times have not been evidently studied in the literature (i.e., if the patient needs to do a blood test, would be better to do it in the early morning). Furthermore, considering rest times of care workers between consecutive working days and other types of required breaks is relatively unexplored in the literature.

Regarding the objective function, most of the researches uses a weighted sum of several objectives. Multi-objective methods should be explored since it helps a decision-maker to find a fair balance between costs and the quality of the service. Moreover, other types of objectives concerning other stakeholders should be considered in multi-objective functions. Indeed, care workers' interests, such as Workload Balance, must also be measured to guarantee an ideal working environment by not overloading care workers.

Most of the studied methods cannot deal with real-world problem sizes (i.e., several hundred patients and care workers) since tested instances are rather small (see Table 7), and some solutions methodologies are costly in computational time. Likewise, there is a need for commonly accepted benchmarks to make possible computational comparisons. However, as explained before, most of the papers deal with real data and real problems that differ within HHC organizations, making it challenging to have benchmark instances since some authors are more concerned with performing all the scheduled activities while others are more concern in providing the best service possible to the patients.

Furthermore, most of the papers study the case of Home Nursing Services, which is a type of HHC. In fact, there is just one paper mentioning an HHU case (Quintanilla et al., 2020). This paper was inspired by a hospital in Spain and considers teams of physicians and nurses visiting patients. However, the teams' characteristics (i.e., number of teams and respective composition) were already pre-established by the hospital, not requiring constraints related to this assignment. HH requires different aspects that are generally not considered in HHC studies, such as assigning physicians and nurses to teams. Moreover, allocating patiens in a more severe case to teams with physicians since physicians are not always available for HH as they usually are shared with other hospital services.

To conclude, there are many aspects of HHC that can be transported to HH and facilitate the logistics process of these units. However, there is room to investigate some specific characteristics of HH that have not yet been much explored.

Chapter 4

Mathematical Model and Solution Approach

Chapter 4 describes the proposed mathematical model and solution approach. Section 4.1 formally describes the problem on which the model is based. Section 4.2 focuses on the detailed description of the proposed mathematical model. Finally, Section 4.4 explores the solution approach proposed to solve the mathematical model and section 4.5 presents the chapter conclusions.

4.1 Problem Description

As explained in the previous chapter, the HHCRSP consists of finding a schedule and route for each care worker to provide the planned care visits over a planning horizon while respecting some constraints. The resulting plan must indicate which visit must be performed by which care worker, in which order, and at what time. In the specific case of HH, patients need to be visited every day, and the available care workers - nurses and physicians - change daily, meaning that it is not possible to assign only one care worker to one patient for all the hospitalization period. For this reason, the three decisions, namely patient assignment, scheduling, and routing, are considered simultaneously. Additionally, in the particular case study of HGO, the planning period is a single day since the number of physicians available is only known on the day itself, as they are shared with other hospital services.

As most of the articles in this field, the problem is modeled as an extension of the VRP, augmented by new constraints specific to this problem. Time windows are not considered since all teams start to work at the same time - beginning of the shift - and cannot finish after the end of the shift. Thus, only this time window is considered to perform all the visits. Furthermore, as all visits are performed during the morning period, the hospital does not see advantages from the patients' perspective on choosing to be visited in the early morning or near lunchtime.

In the problem under study, teams travel by car to a set of locations that represent the patients' homes. All routes start and end at the hospital. Teams can be composed of a single nurse or by one nurse and one physician, depending on the number of physicians available on that day. The number of teams required to perform the home visits depends on the current capacity of the HHU, i.e., the number of vehicles available. All teams start the visits at the same time and cannot finish after the end of the shift. Each patient requires a daily visit from a team since this is an alternative for traditional hospitalization; daily care must be ensured. Some patients require to be the first ones to be visited in the morning due to specific conditions that cannot be predicted and are only known on the planning day. The remaining patients can be visited anytime within the time window for visits.

Additionally, when physicians are not available in all the teams, patients with a more severe case are allocated to teams with physicians. Physicians are all general practitioners, and there is no need to specify qualifications. Nonetheless, nurses may have different specialties that can be matched with the different patients' needs. In addition, nurses are allowed to take a break during the visits period but only after working a certain amount of time.

As was mentioned in Carello et al. (2018), there are mainly three stakeholder perspectives in health care: patients (the quality of service), care workers (fair workloads), and managers (low costs). In our case, the quality of the service is measured through the concept of Continuity of Care, defined as trying to assign the same team to the same patient to create a better relationship with the patient. Fair workloads are also an important measure pointed out by the HHU, which accounts for the balance in the total working time of the teams, i.e., since the teams leave the hospital until they come back again. Lastly, from a management perspective, the low costs, in this case, are only related to Travel Time, and by consequence, travel costs.

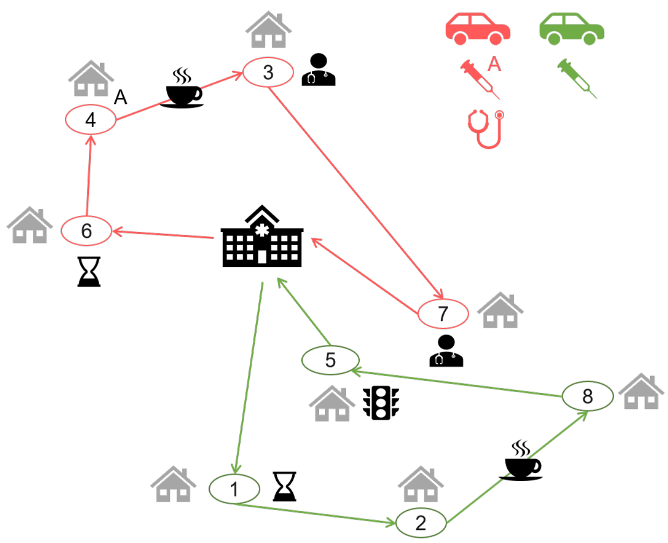

Figure 4.1: Illustrative example of the problem

As a result, two objectives are considered: minimizing Travel Times (1) and maximizing Continuity of Care (2). Even though Workload Balance is not addressed as an objective in the objective function, it is ensured by hard constraints. Considering the three objectives in the objective function would bring a higher complexity to the model, not only from a computational point of view but also for interpreting the results from the HHU side. As Workload Balance must be ensured regardless of any optimization in the other objectives, it was considered in the constraints. Moreover, the HHU mentioned that their main concern was to reduce the Travel Time to reduce costs and accommodate more patients, but at the same time incorporating the Continuity of Care in the model so that the patients perspective is not forgotten. Thus, the problem was modeled in a bi-objective way in order to measure and understand the impact and relation of both objectives: Continuity of Care and Travel Time.

An illustrative example of the problem can be seen in Figure 4.1. There are eight patients, the possibility of forming two teams (two vehicles), two nurses (one is specialized in skill A), and one physician. In this example, patient 1 and 6 require a first -visit in the morning, while patient 5 lives in an area with heavy traffic in the morning. Additionally, patients 3 and 7 need to be seen by a physician, and patient 4 by a nurse with skill A. For this reason, patients 1 and 6 are the first ones to be visited on both routes. Then, patients 3, 4, and 7 are visited by the red team, composed of a physician and a nurse with skill A. Moreover, both teams take a break in the middle of their routes.

4.2 Problem Formulation

The problem is modeled on a directed graph $\mathcal{G} = (\mathcal{N}', A)$, where $\mathcal{N}' = \mathcal{N} \cup 0$ is the node set, $\mathcal{N}= 1, ..., n$ denotes the set of patients to visit in different geographical locations and node 0 represents the hospital location i.e. the depot. A is the arc set between nodes and for an arc $(i, j) \in A$, t_{ij} is the Travel Time from node i to node j. Loops are not allowed.

Let P and E denote the set of physicians and nurses available for HH visits on that day, respectively. Each care worker will have to be assigned to precisely one team $m \in M$ (corresponding to an individual vehicle), and each team can only have at most one nurse $e \in E$ and one physician $p \in P$. Additionally, each nurse $e \in E$ has specific skills $s \in S$.

There are six main types of decision variables. The binary routing variables $X_{ijm} = 1$ if team m goes from patient i to patient j (i.e., if edge $(i, j) \in A$ is included in the tour of team m), and 0 otherwise. The scheduling variables S_{im} define the starting time of the visit of patient i if team m is assigned to this patient; otherwise, S_{im} is zero. The Y_{ijm} binary variable is 1 if team m takes a break between patient i and j (otherwise is 0), while B_m defines the time when each team m takes the break. Finally, the binary assignment variables $Z_{em} \in (0, 1)$ and $Z_{pm} \in (0, 1)$ are equal to 1 when nurse e and physician p are assigned to team m and 0 otherwise, respectively.

The Mixed-Integer Linear Programming (MILP) formulation is presented in detail in the following subsections: Routing (subsection 4.2.1), Scheduling (subsection 4.2.2), Patients requirements (subsection 4.2.4), Workload Balance (subsection 4.2.5) and Objective functions (subsection 4.2.6). In order to facilitate the understanding of the model, the notation is summarized in Table 4.1. The different parameters and auxiliary variables used are going to be explained in more detail in the following subsections. The notation and model can also be found in Appendix A.

Sets and indexes

$\mathcal{N}$	Set of patients (nodes) - $\{1, ..., i, ..., j, ..., n\}$
$\mathcal{N}'$	Set of locations including the hospital location $\{0\} - \{0, ..., n\}$
$\mathcal{M}$	Set of medical teams $\{1, ..., m, ...\}$
$\mathcal{P}$	Set of physicians $\{0, ..., p, ...\}$
E	Set of nurses $\{0, ..., e, ...\}$
S	Set of nurses skills $\{0, ..., s, ...\}$

Decision Variables	
X_{ijm}	1, if medical team m visits patient j after patient i; 0, otherwise (binary)
S_{im}	Start time of medical team m at patient i (positive real)
Y_{ijm}	1, if team m takes a break between patient i and j visits; 0, otherwise (binary)
B_m	Break time of medical team m (positive real)
Z_{pm}	1, if physician p is assigned to medical team m; 0, otherwise (binary)
Z_{em}	1, if nurse e is assigned to medical team m; 0, otherwise (binary)

Parameters	
t_{ij}	Travel Time between patient i and j (positive real)
dur_i	Duration of the visit of patient i (positive real)
K	Big positive real number
startT	Start time of the visits (positive real)
finishT	Maximum finish time of the visits (positive real)
$traffic_i$	1, if patient i lives in a critical region of morning traffic; 0, otherwise (binary)
criticalT	Time until when critical traffic regions cannot be visited (positive real)
breakT	Break duration (positive real)
workBeforeBreak	Time that each team needs to work before taking a break (positive real)
workAfterBreak	Time that each team needs to work after taking a break (positive real)
$first_i$	1, if patient i needs an urgent visit in the morning; 0, otherwise (binary)
q_i	1, if patient i needs to be seen by a physician; 0, otherwise (binary)
r_{is}	1, if patient i needs to be seen by a nurse with skill s; 0, otherwise (binary)
a_{es}	1, if nurse e has skill s; 0, otherwise (binary)
$\|M\|$	Number of vehicles available
δ	Acceptable deviation from the ideal average working time (positive real)
CC_{ip}	Number of times that physician p has been assigned to patient i (positive real)
CC_{ie}	Number of times that nurse e has been assigned to patient i (positive real)

Auxiliary Variables	
w_m	Workload of team m
u_m	Time which team m leaves the hospital
l_m	Time which team m returns to the hospital
$\overline{W}$	Average working time for all teams

Table 4.1: Sets, Parameters, and Decision Variables

4.2.1 Routing

The following constraints (4.1) – (4.3) form the routing constraints based on the VRP (Bredström, Rönnqvist, 2008). Constraints (4.1) ensure that each patient is visited exactly once and by exactly one team. Constraints (4.2) and (4.3) define the routing network, ensuring that each team leaves and arrives at the hospital exactly once (constraint (4.2)), and that each patient is visited and left - flow conservation constraint (4.3).

$$\sum_{m \in M} \sum_{i \in N'} X_{ijm} = 1, \forall j \in N \tag{4.1}$$

$$\sum_{j \in N} X_{0jm} = \sum_{j \in N} X_{j0m} = 1, \forall m \in M \tag{4.2}$$

$$\sum_{j \in N'} X_{ijm} = \sum_{j \in N'} X_{jim}, \forall i \in N', m \in M \tag{4.3}$$

4.2.2 Scheduling

This subsection describes the scheduling constraints, particularly the traffic conditions and the constraints related to the break requirements. All the care workers in the HHU start to work at the same time - defined by the auxiliary variable $startT$, and need to finish before the end of the shift - defined by the auxiliary variable $finishT$. Constraints (4.4) ensure that all visits happen within the period available for visits. Finally, constraints (4.5) ensure that all teams start the visits simultaneously.

There are some regions characterized by heavy morning traffic, and thus, it is not suggested to go to these areas before a particular hour of the morning. This hour is given by the auxiliary variable $criticalT$. For this reason, if a patient i lives in a traffic area, $traffic_i$ is equal to one, and the visits at this patient never start before the $criticalT$ (constraint (4.6)).

Regarding breaks, each team is allowed to have one break (constraint (4.7)), which is assumed to be taken near the patients' house, meaning that there is no need to drive to a break location. The duration of the break is defined by the auxiliary variable $breakT$ and is defined by the hospital. Constraints (4.8) impose that if a team m takes a break between patient i and j, this team must visit these patients (i.e., a break can only happen between two consecutive visits). The break time B_m of each team is defined by constraints (4.9) and (4.10). Moreover, the break should take place between a time window imposed by the working time: the teams should work a certain time before taking a break - $workBeforeBreak$, and the break should not take place as well at the end of the shift. Thus, the teams should work as well a certain time after the break -$workAfterBreak$ (constraints (4.11)).

For each patient, dur_i represents the time needed to perform the care, i.e., the time since the team parks the car until getting in the car again. As said before, the model does not have time windows, and as a consequence, there is no waiting time: a team goes straight from one patient to another and does not have to wait to start the service. Constraints (4.12) and (4.13) ensure the consistency of the patients visits with the break. Constraint (4.12) make sure that a team has enough time between two consecutive patients to perform the visit and travel to the next patient, and constraints (4.13) guarantee that the team goes from one patient immediately to another patient (or after the break, if one is taken at this point), avoiding any waiting times. The set of break constraints was adapted from Xiao et al. (2018) and Trautsamwieser, Hirsch (2014).

$$\sum_{j \in N'} X_{ijm} \cdot startT + t_{0i} \cdot X_{0im} \leq S_{im} \leq \sum_{j \in N'} X_{ijm} \cdot finishT - t_{i0} \cdot X_{i0m}, \forall i \in N, m \in M \tag{4.4}$$

$$S_{im} \leq \sum_{j \in N'} X_{ijm} \cdot startT + t_{0i} \cdot X_{0im} + (1 - X_{0im}) \cdot K, \forall i \in N, m \in M \tag{4.5}$$

$$(S_{im} - criticalT) \cdot traffic_i + (1 - \sum_{j \in N} X_{ijm}) \cdot K \geq 0, \forall i \in N, m \in M \tag{4.6}$$

$$\sum_{i \in N} \sum_{j \in N} Y_{ijm} = 1, \forall m \in M \tag{4.7}$$

$$Y_{ijm} \leq X_{ijm}, \forall i, j \in N, m \in M \tag{4.8}$$

$$S_{im} + dur_i \leq B_m + (1 - \sum_{j \in N} Y_{ijm}) \cdot K, \forall i \in N, m \in M \tag{4.9}$$

$$B_m + breakT \leq S_{jm} + (1 - \sum_{i \in N} Y_{ijm}) \cdot K, \forall j \in N, m \in M \tag{4.10}$$

$$startT + workBeforeBreak \leq B_m \leq finishT + workAfterBreak, \forall m \in M \tag{4.11}$$

$$S_{im} + breakT \cdot Y_{ijm} + (t_{ij} + dur_i) \cdot X_{ijm} \leq S_{jm} + (1 - X_{ijm}) \cdot K, \forall i, j \in N, m \in M \tag{4.12}$$

$$S_{jm} - (1 - X_{ijm}) \cdot K \leq S_{im} + breakT \cdot Y_{ijm} + (t_{ij} + dur_i) \cdot X_{ijm}, \forall i, j \in N, m \in M \tag{4.13}$$

4.2.3 Teams Formation

Apart from the scheduling and routing, the model must assign as well the different available care workers to teams. The team assignment constraints are modeled as follow: constraints (4.14) and (4.15) imply that each available care worker (physicians and nurses, respectively) is assigned to exactly one team. Constraints (4.16) and (4.17) guarantee that each team does not have more than one physician and exactly one nurse, respectively.

$$\sum_{m \in M} Z_{pm} = 1, \forall p \in P \tag{4.14}$$

$$\sum_{m \in M} Z_{em} = 1, \forall e \in E \tag{4.15}$$

$$\sum_{p \in P} Z_{pm} \geq 1, \forall m \in M \tag{4.16}$$

$$\sum_{e \in E} Z_{em} = 1, \forall m \in M \tag{4.17}$$

4.2.4 Patient Requirements

Patient requirements can be divided into three types: early morning visit, patients that need to be seen by a physician, and nurse qualifications. In HH, patients may need an early morning visit due to some unforeseen events. The binary parameter $first_i$ is equal to 1 if the patient i needs a first-visit in the morning, and 0 otherwise. Constraint (4.18) ensure that patients with the need for a first-visit are the first ones to be visited. Furthermore, if it is not possible to have a physician in each team, then, only those teams with one physician can be assigned to patients with parameter $q_i = 1$, which indicates whether patient i needs to be visited by a team with a physician (based on Çakırgil et al. (2020) and Decerle et al. (2018)). Thus, constraint (4.19) ensure that a patient who needs to be seen by a physician is assigned to a team with a physician. Lastly, the parameter r_{is} is 1 if patient i needs to be seen by a nurse with skill s (and 0 otherwise), and a_{es} is 1 if nurse e has skill s (and 0 otherwise). Constraint (4.20) impose that a patient who requires a treatment associated with a specific nurse skill must be visited by a nurse qualified with that skill (based on Çakırgil et al. (2020)).

$$first_i \leq \sum_{m \in M} X_{0im}, \forall i \in N \tag{4.18}$$

$$\sum_{j \in N} X_{ijm} \cdot q_i \leq \sum_{p \in P} Z_{pm}, \forall i \in N, m \in M \tag{4.19}$$

$$\sum_{j \in N'} X_{ijm} \cdot r_{is} \leq \sum_{e \in E} Z_{em} \cdot a_{es}, \forall i \in N, m \in M, s \in S \tag{4.20}$$

4.2.5 Workload Balance

Another aspect to be considered in this model regards the working time definition and balance. The auxiliary variable working time w_m of a team m is defined as the interval of time between the time that a team m leaves (l_m) and arrives (u_m) at the hospital. Expressions (4.21) - (4.23) summarize these computations (based on Decerle et al. (2017)).

To balance the working times within teams, an auxiliary variable named average working time $\overline{W}$

is computed by adding the working time of all teams and dividing by the number of teams (which corresponds to the number of vehicles available, |M|) (expression (4.24)). Then, the working time w_m for all teams must be within the average plus or minus an acceptable deviation δ agreed with the hospital (constraints (4.25)) (based on Hertz, Lahrichi (2009)).

$$S_{im} - t_{0i} + (X_{0im} - 1) \cdot K \leq l_m \leq S_{im} - t_{0i} - (X_{0im} - 1) \cdot K, \forall i \in N, m \in M \tag{4.21}$$

$$S_{im} + dur_i + t_{i0} + (X_{i0m} - 1) \cdot K \leq u_m \leq S_{im} + dur_i + t_{i0} - (X_{i0m} - 1) \cdot K, \forall i \in N, m \in M \tag{4.22}$$

$$w_m = u_m - l_m, \forall m \in M \tag{4.23}$$

$$\overline{W} = \frac{\sum_{m \in M} \times w_m}{|M|} \tag{4.24}$$

$$\overline{W} - \delta \leq w_m \leq \overline{W} + \delta, \forall m \in M \tag{4.25}$$

4.2.6 Objective functions

The problem aims to optimize two different objectives. The first objective function (4.26) seeks to minimize the total Travel Time incurred by the medical teams, while the second (4.27) concerns the quality of the service, which is measured by the Continuity of Care. The Continuity of Care objective seeks to maximize the connection between care workers and patients. To measure the Continuity of Care, parameters CC_{ip} and CC_{ie} are used for physicians and nurses, respectively. The parameter is based on the number of times care work (physician p or nurse e) has been assigned to patient i in the past. Thus, the higher the value of the parameter, the higher the connection between care worker and patient. By maximizing these two parameters, the model is going to assign to a patient the care workers who visited him/her the most.

$$min \sum_{m \in M} \sum_{i \in N} \sum_{j \in N'} X_{ijm} \cdot t_{ij} \tag{4.26}$$

$$max \sum_{p \in P} \sum_{i \in N} \left(CC_{ip} \cdot \sum_{m \in M} \left(\sum_{j \in N'} X_{ijm} \cdot Z_{pm} \right) \right) + \sum_{e \in E} \sum_{i \in N} \left(CC_{ie} \cdot \sum_{m \in M} \left(\sum_{j \in N'} X_{ijm} \cdot Z_{em} \right) \right) \tag{4.27}$$

In order to obtain a MILP model, the objective function 2 must be linearized as follows:

$$max \sum_{p \in P} \sum_{i \in N} \left(CC_{ip} \cdot \sum_{m \in M} g_{ipm} \right) + \sum_{e \in E} \sum_{i \in N} \left(CC_{ie} \cdot \sum_{m \in M} g_{iem} \right)$$

Where the auxiliary binary variables $g_{ipm}, \ \forall i \in N, p \in P, m \in M$ and $g_{iem}, \ \forall i \in N, e \in E, m \in M$

are defined through the following constraints:

$$g_{ipm} - \sum_{j \in N'} X_{ijm} \leq 0 \qquad\qquad g_{iem} - \sum_{j \in N'} X_{ijm} \leq 0,$$

$$g_{ipm} - Z_{pm} \leq 0 \qquad\qquad g_{iem} - Z_{em} \leq 0$$

$$g_{ipm} - \sum_{j \in N'} X_{ijm} - Z_{pm} + 1 \geq 0 \qquad\qquad g_{iem} - \sum_{j \in N'} X_{ijm} - Z_{em} + 1 \geq 0$$

4.3 Relationship with the literature

The literature in HHC regarding scheduling and routing decisions is quite vast. However, most of the papers deal with home nursing services and not HHUs. Even though the general planning is similar, and some features are the same, there are aspects related to HHUs that are not considered in HHC problems. For instance, instead of having nurses visiting patients, visits are done by teams composed of physicians and nurses. In addition, patients have different care requirements than HHC services since they require the same type of care as they would have in a hospital. Thus, some patients may need to be seen by a physician depending on the patient's status, or patients may need to be seen in the early morning (first-visit) to do a blood test, for example.

As far as the author is aware, only one paper in the literature handles the case of an HHU (Quintanilla et al., 2020). Even though Quintanilla et al. (2020) consider teams visiting patients, these teams are already set by the hospital. By contrast, in the HGO case, physicians are shared with other hospital units, and it is not possible to predict if there are physicians available on a specific day, meaning that teams' formation needs to happen every day. Additionally, Quintanilla et al. (2020) does not consider Continuity of Care with teams and patients, some relevant features to explore in this case study.

Another lack in the literature regards the use of multi-objective functions to incorporate the interests of the various stakeholders. Nevertheless, some papers have already considered the three features: Continuity of Care, Workload Balance, and Travel Time; simultaneously in their models. Martinez et al. (2018), addresses the problem in two different phases. In the first phase, for each patient, a set of know care workers is built to account for the Continuity of Care. In a second phase, Travel and waiting times are minimized, considering that the patients can only be assigned to the known care workers. Workload Balance is only considered when more than one care worker qualifies to be assigned to the patient. Thus, the chosen care worker is the one that has the shortest working time. Yalçındağ et al. (2016a), also refer to these three features. Nevertheless, Continuity of Care is ensured through a hard constraint, meaning that a unique care worker is assigned to each patient over the planning horizon, not allowing for flexibility. Once more, a two-stage approach is proposed: on the first stage, Workload Balance is optimized, and on the second stage, the Travel Time. Gomes, Ramos (2019) also treats the problem as two independent sub-problems. One sub-problem that assigns teams to patients in a MO way, considering Travel Times and Workload Balance. Here, the loyalty between caregivers and patients is ensured through soft-constraints, aiming to assign the same team to the same patient. The second sub-problem assigns caregivers to teams. Thus, as in this master thesis, Gomes, Ramos (2019) addresses the aspect of teams' formation. An aspect which is not commonly addressed in the literature.

The only paper which considers the three features simultaneously as in our approach, without taking different stages, is Milburn, Spicer (2013). Milburn, Spicer (2013) considers a Multiple-Objective (MO) function with three different objectives, one for each feature. Continuity of care is measured through nurse consistency, i.e., the total number of different nurses seen by patients, and Workload Balance by the number of patients assigned to each care worker. However, in this paper, remote monitoring devices are used, which can substitute a nurse visit, enabling the improvement of the objectives considered.

There have been emerging some papers considering Continuity of Care. Most of them use hard constraints, forcing a patient to be visited by a specific care worker or limiting the number of different nurses assigned to each patient. Similar papers that also addressed Continuity of Care in the objective function were Grenouilleau et al. (2019), and Nickel et al. (2012). Nickel et al. (2012) uses a score that accounts for the number of different nurses that have visited a patient, while Grenouilleau et al. (2019) have a similar approach to our model, using a function based on the number of times a care worker has been assigned to a patient's past visits. However, the function has only three different values, for 0; 1 and 2; and more than 2 visits. Thus, for more than two visits, the value of the function is always the same. In our proposed model, it is the first time a total score is considered, accounting for all past visits of a care worker to a patient, aiming to assign the care worker with the highest number of visits with the respective patient.

Table 4.2 shows a summary and comparison, in terms of features and objective functions, of the most similar papers to the current dissertation. In conclusion, the model described in this master thesis makes three primary contributions to the literature in the HHCRSP:

1. The use of a MO function accounting for Continuity of Care and Travel Time, enabling a trade-off study between these two features, and considering at the same time the feature Workload Balance.

2. The measure used for the Continuity of Care, accounting for all the times a care worker has visited a patient. Furthermore, aiming to maximize this value for both nurses and physicians.

3. The consideration of an HHU with specific characteristics, namely teams' formation, first-visit requirements, and the need to be seen by a physician.

	Features			Teams		WB		CC		TT	Objective Function		
Papers	**FV**	**Breaks**	**Skills**	**Assig.**	**Form.**	**Const.**	**Objec.**	**Const.**	**Objec.**	**Objec.**	**SO**	**WS**	**MO**
Gomes, Ramos (2019)		X		X	X		X	X		X			X
Grenouilleau et al. (2019)			X						X	X		X	
Liu et al. (2018)			X	X				X		X			X
Martinez et al. (2018)			X			X		X		X	X		
Milburn, Spicer (2013)							X		X	X			X
Nickel et al. (2012)			X						X	X		X	
Quintanilla et al. (2020)	X		X	X		X				X	X		
Yalçındağ et al. (2016a)			X				X	X		X	X		
This dissertation	**X**	**X**	**X**	**X**	**X**	**X**			**X**	**X**			**X**

FV – First-Visit; Assig. – Assignment, Form. – Formation; Const. – Constraint; Objec. – Objective; SO – Single-Objective; WS – Weighted Sum; MO – Multi-Objective

Table 4.2: Summary and comparison of the most similar papers to the present dissertation.

4.4 Solution approach

When an optimization problem involves only one objective function, the task of finding an optimal solution is called Single-Objective Optimization Problem (SOOP). Nevertheless, most of the real-world problems involve different and possibly conflicting objectives. In this context, the concept of optimal solution does not exist, and instead, the concept of non-dominated solution or Pareto optimal solution is used. The task of finding one or more Pareto optimal solutions is known as Multiple-Objective Optimization Problem (MOOP). From a management perspective, MOOP is also known as Multiple Criteria Decision-Making (MCDM) (Deb, 2001).

Figure 4.2 shows two different procedures based on Deb (2001) to cope with MOOP. On the one hand, if a relative preference among the objectives is known, a composite function as a weighted sum of objectives can be used (Figure 4.2, top). In this case, a weight is assigned to each objective, depending on the preference of that objective to the decision-maker. Thus, the MOOP is converted into a SOOP. In this procedure, a higher level of information is used to set the weights' vector. Although this procedure is the most widely used due to its simplicity, it can be challenging to set the weights' vector for the objectives. Furthermore, it can be subjective as it depends on the weights being used and can bring loss of information since everything is summarized into a single score (Liu et al., 2018; Deb, 2001).

On the other hand, in the second procedure (Figure 4.2, bottom), the higher-level of information is used to choose between a set of trade-off solutions. The difference relies on when the higher information is used. Asking a decision-maker to define a weight vector can be challenging and not straightforward, even more, when we do not know the potential trade-off solutions yet. In MOOP, the effort should be made in finding the set of trade-off or Pareto optimal solutions considering all objectives. Only after, with higher-level qualitative information and experience-driven, the decision-maker can make a choice (Deb, 2001).

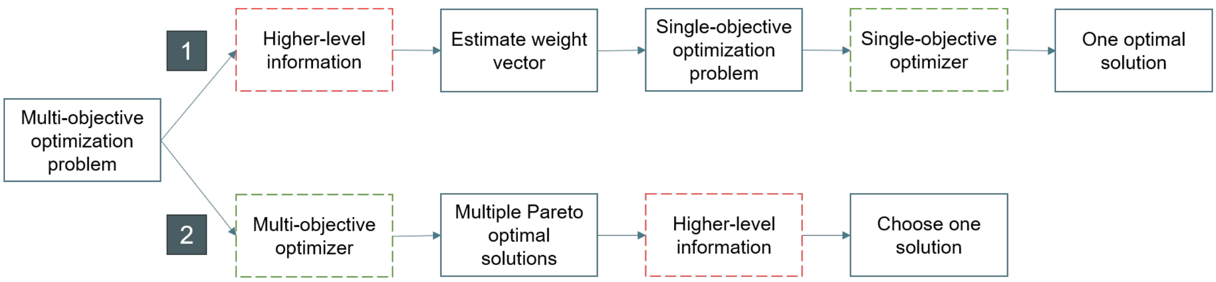

Figure 4.2: Two different procedures for MOOP

With all this in consideration, this dissertation's solution approach can be seen in Figure 4.3. To handle the inherent MOOP, the ϵ-constraint method (subsection 4.4.2) is going to be used to generate multiple trade-off solutions and find the Pareto front. After having the Pareto front, two different paths can be followed. The first one (Figure 4.3, top) uses the crowding distance metric (subsection 4.4.3) to provide a smaller number of non-dominated solutions to the decision-maker. For more efficient decision making, a set of uniformly distributed solutions is commonly wanted (Fu, Wen, 2017). At this stage, the decision-maker may use his/her knowledge to compare the provided solutions and decide on the best one.

Nevertheless, the decision-maker may not always be present to decide on the best solution, or it might still be difficult to choose only one solution. At this point, a method for MCDM should be used to obtain a ranking of the solutions. The method applied was TOPSIS (subsection 4.4.4), which allow to obtain a final solution from the initial Pareto front. Ideally, a more detailed multi-criteria decision analysis should be explored together with the decision-maker. However, it was not possible to discuss further with the decision-maker, so this technique was chosen since only weights for the objectives are needed. The decision-maker's high-level information and input would be fundamental to determine the weights used in this method.

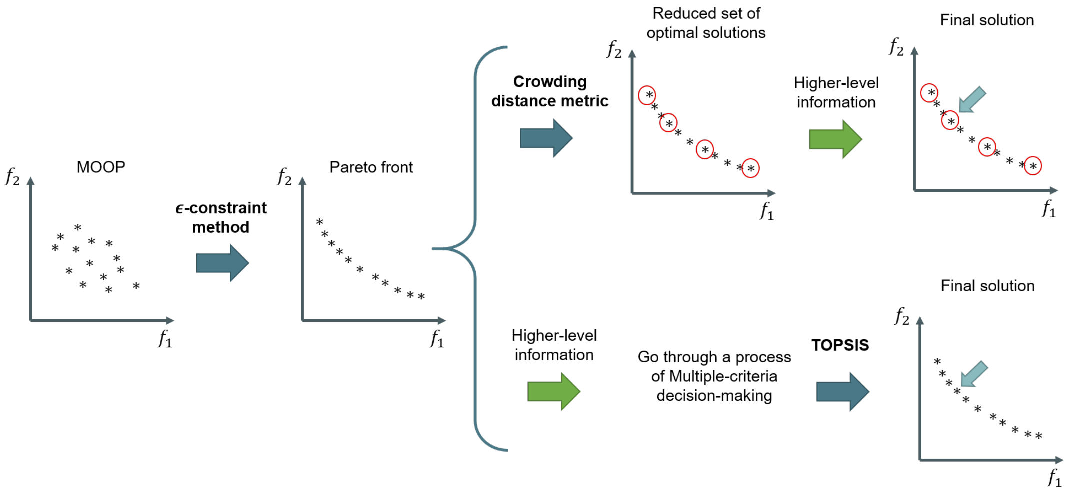

Figure 4.3: Schematic solution approach for the MOOP

4.4.1 Multi-Objective Optimization Problem

This dissertation addresses a special case of a MOOP, namely the Bi-Objective Optimization Problem (BOOP). General BOOP are formulated as follows (Bérubé, Gendreau, 2007; Fu, Wen, 2017):

$$min\ f(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x})), \quad \vec{x} \in \chi$$

$$s.t.\ \ c(x) \leq 0,$$

Where the vector $x = (x_1, x_2, ..., x_n)^T$ consists of n optimization variables; $f_1(\vec{x})$ and $f_2(\vec{x})$ are the two objective functions; χ is the set of feasible solutions in the decision space (including the lower and upper bounds) and $c(x)$ includes the constraints. Figure 4.4 illustrates the decision and objective space. Each calculation of vector $f(\vec{x})$ can be denoted as $\vec{z}$. Thus, the objective space can defined by:

$$Z = \{\vec{z} = (z_1, z_2) : z_i = f_i(\vec{x}),\ \forall \vec{x} \in \chi, i = 1, 2\}$$

As there are two objectives to optimize, it may not exist a solution that optimizes both simultaneously. Thus, instead of an optimal solution, one will search for an acceptable trade-off, where there is no strictly better solution, and it is not possible to improve the value of one objective function without worsening the value of the other one. The concept of the optimal solution in SOOP is then replaced by the concept of

Pareto efficiency in MOOP (Bérubé, Gendreau, 2007). The optimal trade-off solutions among objectives constitute the Pareto front.

The solutions on the Pareto front are also called non-dominated solutions. A solution $x^{(1)}$ dominates another solution $x^{(2)}$ if solution $x^{(1)}$ is no worse than $x^{(2)}$ in all objectives (i) and is strictly better than $x^{(2)}$ in at least one objective (ii). In this case it is possible to state that $x^{(2)}$ is dominated by $x^{(1)}$. The domination concept for a minimization problem can be defined as follows (Fu, Wen, 2017),

$$x_1 \prec x_2,$$

$$iff \quad (i)\;\; f_i(x_1) \leq f_i(x_2), \;\; \forall i \,\epsilon\, [1, n],$$

$$(ii)\;\; f_i(x_1) < f_i(x_2), \;\; \exists i \,\epsilon\, [1, n],$$

where $\prec$ means domination for the minimization problem. When it is not possible to conclude whether a solution dominates another, those solutions are non-dominated with respect to each other. The solutions that are not dominated by any other solution in the set of feasible solutions form the non-dominated or efficient set and belong to the Pareto front.

There is one optimal value in the SOOP for each of the two conflicting objective functions. These optimal values define the Ideal objective vector $\vec{z}^I = (z_1^I, z_2^I)$, which can be used as a reference point since it denotes a lower bound for the objective function (in a minimization problem). By contrast, the Nadir objective vector $\vec{z}^N = (z_1^N, z_2^N)$ correspond to the solution value when the opposite objective is equal to its Ideal value. Thus, Nadir points define the upper bounds (in a minimization problem) on the value of efficient solutions (Liu et al., 2018; Bérubé, Gendreau, 2007; Deb, 2001). The graph on the right side in Figure 4.4 illustrates an objective space for a bi-objective minimization problem where it is possible to see the Ideal and Nadir vectors.

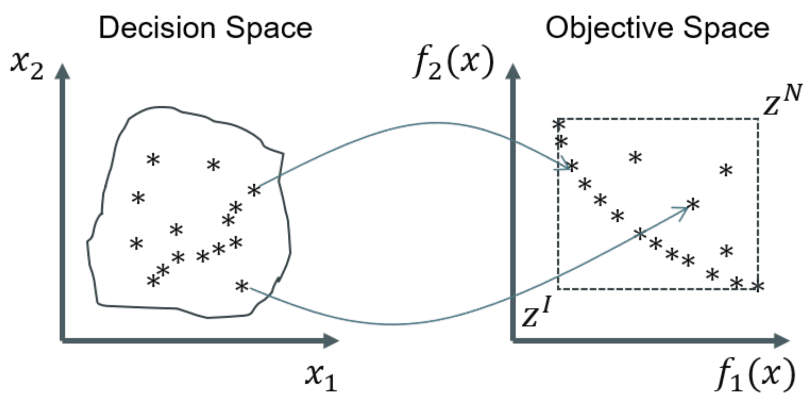

Figure 4.4: Mapping of solutions from the decision space to the objective space

In order to obtain the Pareto front for a MOOP, the preferred procedure is to weigh the individual objective functions with different weight coefficients – weighted sum method. Changing the weight coefficients makes it possible to obtain different solutions and find the entire Pareto front. Even though this method is easy to implement, many scenarios need to be run to get the Pareto front. Additionally, this approach cannot cover non-convex Pareto fronts, resulting in an incomplete exploration of the solution space (Park et al., 2015; Deb, 2001; Fu, Wen, 2017).

4.4.2 ϵ-constraint method

The ϵ-constraint method was developed to find the Pareto front of MOOPs. This method generates single objective subproblems, called ϵ-constraint problems - $P_k(\epsilon)$, by selecting one objective to be minimized or maximized, while transforming the remaining objectives in constraints to be less/more or equal to a given target value - ϵ_j (Park et al., 2015; Bérubé, Gendreau, 2007). For a minimization BOOP, the $P_i(\epsilon_j)$ are:

$$min\ f_i(\vec{x})$$

$$s.t.: f_j(\vec{x}) \leq \epsilon_j,$$

$$i, j = 1, 2 \quad \text{and} \quad i \neq j,$$

$$\vec{x} \in X$$

The parameter ϵ_j defines an upper bound of the value of the objective function f_j, which is set as a constraint. The idea is to construct a sequence of $P_i(\epsilon_j)$ problems based on a progressive reduction of ϵ_j. The exact Pareto front can be found by solving ϵ-constraint subproblems, as long as we know how to modify ϵ_j. Contrarily to the weighted sum, this method can be used to achieve efficient points in a non-convex objective space (Park et al., 2015; Deb, 2001).

One disadvantage pointed out for the ϵ-constraint method is that the solution depends on the ϵ_j vector and how this vector is chosen, meaning that one will need some apriori knowledge and information to apply the method (Deb, 2001). Nevertheless, as one of the objective functions - Continuity of Care - considered in our model only takes integer values, this objective can be used as a constraint, making it easier to define and vary the ϵ_j vector.

Algorithm 1 describes the procedure to find the Pareto front using the ϵ-method based on Bérubé, Gendreau (2007). The proposed algorithm starts by computing the Ideal and Nadir values of both objectives. Then, starting from one of the solutions (z_i^I, z_j^N), we solve successive $P_i(\epsilon_j)$ subproblems. The ϵ_j is changed by a constant value ($\triangle$) through the expression $\epsilon_j = z_j^N - \triangle$, until ϵ_j reaches its Ideal value z_j^I. The solutions found on the successive subproblems are added to the Pareto front, and in the end, all the dominated alternatives are eliminated.

Algorithm 1 Pareto front computation for a minimization BOOP - based on Bérubé, Gendreau (2007)

1: Compute the ideal values z_1^I and z_2^I
2: Compute the Nadir points z_1^N and z_2^N
3: Add (z_i^I, z_j^N) to the Pareto Front and set $\epsilon_j = z_j^N - \triangle$
4: **while** $\epsilon_j \geq z_j^I$ **do**
5:     Solve $P_i(\epsilon_j)$
6:     Add the optimal solution (z_i^*, z_j^*) to the Pareto Front
7:     Set $\epsilon_j = z_j^* - \triangle$
8: Remove dominated points from the Pareto Front if needed

4.4.3 Crowding Distance metric

One of the main goals of multi-objective optimization is to find the Pareto front. Nevertheless, for more efficient decision making, a set of uniformly distributed Pareto solutions is also essential to prevent having to choose between "very similar" alternatives. Furthermore, it can also be useful to provide a reduced, yet diverse, number of choices to the decision-maker when he/she needs to choose the final solution.

Crowding distance is a widely used metric to compare non-dominated solutions in the same Pareto-front, based on the extent of their proximity with other solutions (Deb et al., 2002; Fu, Wen, 2017). It is a density-estimation metric that estimates the density of solutions surrounding a particular solution in the objective space. For example, this metric is used when creating new individuals during genetic algorithm evolution. Thus, the selected set must preserve the solutions' diversity (Deb et al., 2002).

Figure 4.5 illustrates the crowding-distance computation, for which the procedure can be seen in Algorithm 2. By observing Fig 4.5, the crowding distance of point p is the estimate of the average size length of the cuboid enclosing p, using the nearest neighbors as the vertices, and without including any other point (Deb et al., 2002).

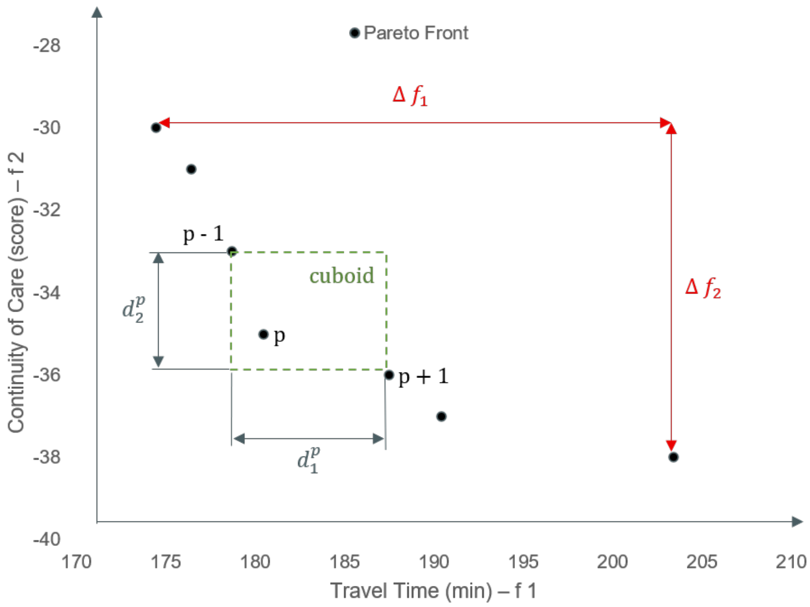

Figure 4.5: Estimation of the crowding distance for a solution p

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Algorithm 2 Crowding distance computation for a Bi-objective problem - based on Deb et al. (2002)

1: Sort the set of non-dominated solutions in ascending order of the objective function i
2: Assigned an infinite crowding distance value to the boundary solutions
3: Compute $\Delta z_i = \left| z_i^{max} - z_i^{min} \right|, i = 1, 2,$ where z_i^{max} and z_i^{min} are the maximum and minimum values of the ith objective function.
4: For each intermediate solution p compute $d_i^p = \left| z_i^{p+1} - z_i^{p-1} \right|, i = 1, 2$
5: Calculate the crowding distance value, Δ_p, for each intermediate solution, where $\Delta_p = \sum_{i=1}^{2} \frac{d_i^p}{\Delta z_i}$
6: Rank the non-dominated solutions in descending value of crowding distance. Solutions with a higher value of crowding distance are preferred.

As explained in Algorithm 2, the boundary solutions with the smallest and largest objective function values have an infinite value of crowding distance, so they are always selected. Thus, the calculation of the crowding distance is only needed for intermediate solutions. Note as well that each objective function is normalized before calculating the crowding distance for intermediate solutions.

4.4.4 TOPSIS method

In order to help the decision-maker evaluate and select the best choice among a set of solutions, MCDM methods can be used. In this case, the computational method of decision-making used is TOPSIS developed by Hwang, Yoon (1981). The principle behind this method is to choose the option which is closer to the "ideal" solution and the farthest possible to the "negative-ideal" solution. The ideal solution corresponds to the solution with the best values achieved by each criterion, whereas the negative-ideal solution consists of the worst values (Opricovic, Tzeng, 2004; Hwang, Yoon, 1981). The distances to the ideal and negative-ideal solutions are computed using the Euclidean distance. The procedure can be seen in the Algorithm 3.

Algorithm 3 TOPSIS procedure - based on Hwang, Yoon (1981)

1: Calculate the normalized decision matrix R where $r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{J} f_{ij}^2}}, j = 1, ..., J; i = 1, ..., n.$

2: Calculate the weighted normalized decision matrix V where $v_{ij} = wi * rij, j = 1, ..., J; i = 1, ..., n,$ and w_i is the weight of the ith criterion ($\sum_{i=1}^{n} w_i = 1$).

3: Determine the ideal (A*) and negative-ideal (A-) solutions.

A* $= \{v_1^*, ..., v_n^*\} = \left\{(\underset{j}{max}\, v_{ij} \mid i\epsilon I'), (\underset{j}{min}\, v_{ij} \mid i\epsilon I'')\right\}$

A- $= \{v_1^-, ..., v_n^-\} = \left\{(\underset{j}{min}\, v_{ij} \mid i\epsilon I'), (\underset{j}{max}\, v_{ij} \mid i\epsilon I'')\right\}$

Where I' represents a criterion that we want to maximize and I" a criterion we want to minimize.

4: Calculate the separation of each alternative from the ideal solution (S_j^*) and the negative-ideal solution (S_j^-) using the Euclidean distance.

$S_j^* = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_{ij}^*)^2}, j = 1, ..., J$

$S_j^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_{ij}^-)^2}, j = 1, ..., J$

5: Calculate the relative closeness to the ideal solution defined as $C_j^* = \frac{S_j^-}{S_j^* + S_j^-}, j = 1, ..., J.$

6: Rank the solutions from the largest to the smallest value of C_j^*. The solution with the largest value of C_j^* is the best solution according to the TOPSIS method.

TOPSIS uses vector normalization to transform the various criteria dimensions into non-dimensional criteria, to enable a comparison (Opricovic, Tzeng, 2004; Hwang, Yoon, 1981). Additionally, it is necessary to determine weights for the different criteria so that the decision-maker could express his/her preferences in terms of the relative importance of criteria. In this stage, it would be important to tune these values with the decision-maker since the final solution depends on the vector of weights. Methods for weight assessment should be used. Nevertheless, it was not possible to apply those methods in our case study since it was not possible to discuss this further with the decision-maker. For this reason, in this dissertation, we use weights of 1/2 and 1/2 for both objectives simply to show, in this case, which solution would be chosen by the TOPSIS method.

This method is widely used in decision making due to its simplicity and efficient computation. However, some problems have been pointed out to this method since it uses normalized values by vector normalization, which may depend on the evaluation unit. To face this challenge, linear normalization can be introduced (Opricovic, Tzeng, 2004). Additionally, TOPSIS determines a solution with the shortest distance to the "ideal" solution and the greatest distance from the "negative-ideal" solution. Still, it does not consider the relative importance of these distances (Opricovic, Tzeng, 2004). As a result, a solution with a higher distance from the "ideal" solution but also with a higher distance from the "negative-ideal" solution is ranked better than other solutions closer to the "ideal" solution but closer as well to the "negative-ideal" solution.

4.5 Chapter conclusions

This chapter describes the mathematical model developed to provide feasible schedules and routes for an HHU. The mathematical model was built in the context of HH and incorporates features that were not commonly considered in the literature, such as teams' formation, the need for physicians, and first -visit in the morning. Additionally, the three different stakeholders perspectives – patients, care workers, and managers – are taken into consideration, either in the objective functions: Travel Time and Continuity of Care; or guaranteed by the constraints of the model: Workload Balance. The model can be easily adapted for other HHUs since all features (ex. starting time, length of the break, number of vehicles, nurses' skills) can be easily modified.

Furthermore, having a model which indicates the starting time of each visit can also help in other practical aspect of HH. For instance, if a patient calls to the HHU to know what time (s)he is going to be visited, the HHU can provide a precise answer (a common thing happening in the daily basis of the unit). The model could be also incorporate in a platform that would send the notification of time of the visits to the patients, improving the quality and increasing the confidence in the service.

The proposed solution approach starts by finding the Pareto front of the two conflicting objectives using the ϵ-constraint method. In this way, the decision-maker does not need to decide yet on the weights of the different objectives, which may be subjective and challenging. Then, two paths were discussed. The first one uses the crowding distance method to reduce the number of solutions provided to the decision-maker to facilitate his/her final choice. The second path consists of using an MCDM method and, together with the decision-maker, decide on weights for the different criteria so that a final solution is computed. The proposed method was TOPSIS. However, it was not possible to develop an MCDM analysis with the decision-maker. The importance of the decision-maker in the final steps of the solution approach would be crucial. Nevertheless, this second approach allows, if necessary, to obtain a single final solution with only a few additional computations.

Chapter 5

Numerical Experiments

This chapter presents an overview of the numerical experiments and discusses the main results obtained with the proposed solution approach. Experiments were conducted on real-world instances provided by HGO and on instances derived from the literature. All algorithms were coded in C++. For solving MILPs, IBM ILOG CPLEX C++ Concert Technology version 12.9 was used. The chapter includes two main sections, starting with section 5.1, which describes the real-world instances and the application of the proposed solution approach in those instances. The second section 5.2 describes the literature instances and the model's computational performance on the respective instances.

5.1 Real-world instances

This work considers a real-world setting from the HHU of HGO, the case under study. A month of manual records from the HHU was provided, which corresponds to December 2019. These instances are representative in size and features for most of the HHUs in Portugal. A manual solution of a week is used to evaluate and compare the results provided by the model. These records indicate, for each day, all the nurses' visits, the corresponding starting time, and duration. Additionally, patients locations were provided in order to construct the Travel Time's matrix.

Nevertheless, the data provided is not enough to test the whole model. There is no information regarding physicians' visits, traffic zones, and first-visit requests. Furthermore, information regarding breaks and skills was not available since these features are not considered in the actual planning but is something the unit aims to incorporate. For this reason, a simplified model was used to run these instances and make a comparative analysis with the current planning. The simplified model comprises the two objective functions (4.26) and (4.27), without considering the physicians' parameters; constraints (4.1) to (4.5); constraints (4.12) and (4.13) without the break parameter; constraints (4.15) and (4.17); and Workload Balance constraints (4.21) to (4.25).

There are 7 instances corresponding to a 7-day period from December 13 to December 19. On each day, there were 3 nurses and between 13 to 18 patients. The services' duration varies from 25 to 60 minutes. Locations correspond to patients real locations, and the Travel Time between patients was calculated using the postal-codes of the patients and Google Maps API, with the mode driving and traffic model equal to best guess (Google, 2020). Note that the Travel Time matrix is non-symmetric since it corresponds to real Travel Times. Additionally, the variables $startT$ and $finishT$ were established as 9 am and 3 pm, respectively, corresponding to the current schedule of the HHU. The parameter δ, used to control the Workload Balance, was set by the HHU as 15 minutes, which means the maximum difference in working time between teams cannot be more than 30 minutes.

The Continuity of Care score was computed taking into account the number of times a nurse visited a patient. For the first day of the test week, that is, for December 13, the Continuity of Care score was computed considering the assignments until that day. After December 13, the score was updated according to the solution given by the model, in order to see the improvement in Continuity of Care over a week. Thus, the Continuity of Care scores changes from the manual solution to the model solution since, in each instance, the assignment results from the manual and model solution may not necessarily be the same.

In the following subsection 5.1.1, a Single-Objective analysis is performed for both objective functions. Then subsection 5.1.2 shows an illustration of the solution approach presented in the previous chapter applied to the real-world instances. Lastly, subsection 5.1.3 represents the overall experiments applied to the real-world instances.

5.1.1 Single-Objective analysis

Before approaching the bi-objective model, a single objective analysis was performed to understand the model's behavior in each of the objectives. The model was solved for each objective individually using CPLEX with a time limit of 3600 seconds. Table 5.1 shows the performance results for a SOOP. The gap represents the difference between the solution found and the current best bound, meaning that to prove optimality, a gap of 0% is needed. The name of the different instances on the table corresponds to the day from which the data was retrieved. For example, instance 13.12 corresponds to the HHU' data of December 13 (i.e., patients visits, duration, and nurses available).

		Min. Travel Time		Max. Continuity of Care	
Instance	**Number of patients**	**GAP (%)**	**Computation Time (s)**	**GAP (%)**	**Computation Time (s)**
13.12	18	12.24	3600.00	0.00	9.21
14.12	17	12.78	3600.00	0.00	13.59
15.12	18	11.82	3600.00	0.00	14.88
16.12	18	10.81	3600.00	0.00	5.29
17.12	14	6.96	3600.00	0.00	4.74
18.12	14	0.00	1486.16	4.35	3600.00
19.12	13	0.00	877.04	0.00	46.03
Average	16	7.56	2909.03	0.62	527.68

Table 5.1: Performance results for the SOO

For the objective Continuity of Care, it is possible to have an optimal solution with a short computational time. Only on instance 18.12 CPLEX was not able to prove the optimality of the given solution. By contrast, for the Travel Time objective, an optimal solution is only found for two of the 7 instances within a running time of 3600 seconds. Thus, only for the two smallest instances with 13 and 14 patients, it was possible to find an optimal solution. Some experiments were done to try to understand which could be influencing the computational time. Instance 17.12 and 18.12 have the same number of patients. What changes within the instances is the Travel Time matrix since the patients are different; thus, locations are different, and the Continuity of Care scores within patients and nurses. Using the Travel Time matrix of instance 18.12, and the remaining characteristics of instance 17.12, the Continuity of Care optimal solution was reached in 3 seconds. After analyzing the Continuity of Care score of instance 18.12, it was possible to realize that a new nurse was introduced on this day, meaning that all Continuity of Care scores were zero for this nurse. This increases the assignment possibilities and may increase the computation time. By contrast, using the Travel Time matrix of instance 17.12 and the characteristics of instance 18.12 and optimizing Travel Time, the computational time was 3600 seconds and a gap of 6%. Alternatively, using the Travel Time matrix of 18.12 and the characteristics of instance 17.12, the computational time was around 1000 seconds. Thus, the computation time when minimizing the Travel Time objective seems to be highly dependent on the Travel Time matrix's complexity.

The VRP, which is a subpart of the problem studied in this work, is an NP-hard problem, and the length of time it takes to solve grows with the size of the problem, making it difficult to arrive the optimality within a short period. Figure 5.1 represents the evolution of the gap between the best bound and the current solution, with the computation time, for the objective Travel Time (see Table B.1 for the correspondent table). The green line represents the average evolution for instances with 17 and 18 patients (instances December 13 to December 16), while the line in blue represents the average evolution for instances with 13 and 14 patients. It is possible to see that by only increasing the patients from 13-14 to 17-18, the average gap after 1080 seconds increases from 3.42% to 13.92%. However, it is also possible to conclude that the gap stabilizes, in the sense that it decreases slowly, after this time, meaning that running the model for 1080 seconds or 3600 seconds could lead to more or less the same results. Thus, it could be sufficient to run the model only for 1080 seconds (i.e., 18 minutes), from a practical point of view. In this way, the quality of the solution would not be compromised too much, and the results could be obtained faster.

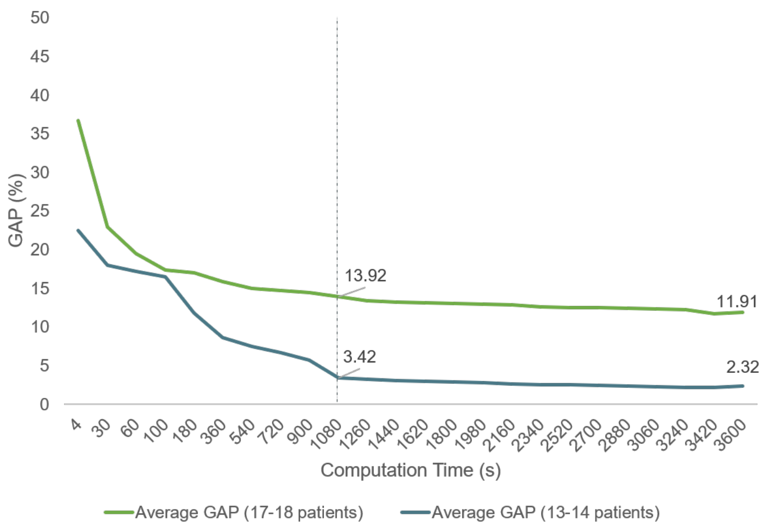


Figure 5.1: Evolution of the gap with the computation time for the SOOP with the Travel Time

The graph in Figure 5.2 shows the percentage of improvement that the model allows in comparison with the current solution adopted by the hospital (refer to Table B.2 in the appendix for more detailed data). In a single objective perspective, the Travel Time improvements range from 2.93 to 21.51% for the tested instances. As the hospital's operation area is relatively small, the improvements in Travel Time are limited to an extent. Nevertheless, more significant improvements can be achieved in the second objective, with the average increase in Continuity of Care of 37.11%.

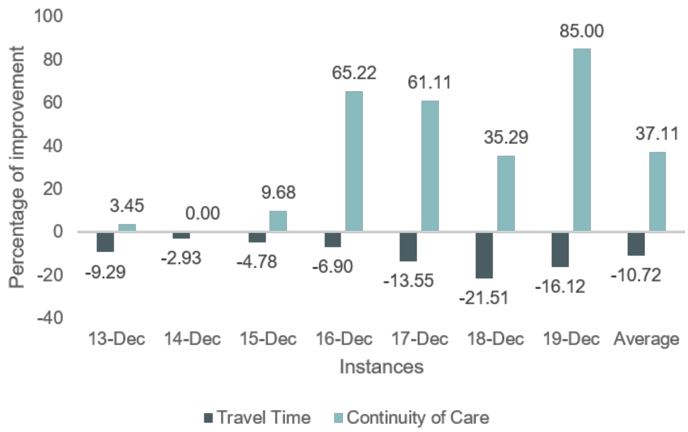


Figure 5.2: Improvements in the single-objective values in relation to the current manual solution

The impact of the Workload Balance in the two objectives was also studied to better understand, alongside the HHU, which could be the best value for δ (i.e., the maximum deviation from the ideal average working time, which allows a difference in working times within teams). Figure 5.3 shows this analysis for the average of all instances. Table B.4 in the appendix shows the detailed solutions for all instances, while Table B.3 summarizes the average data, originating the graphs in Figure 5.3. The graph on the left side is related to Travel Time, while the one on the right represents the impact on Continuity of Care. The horizontal axis on both graphs represents the maximum working time difference allowed, meaning that if this value is 30 minutes, the teams can only work more or less 15 minutes - δ - than the average working time of all teams. Thus, the maximum difference in working time - secondary vertical axis - cannot exceed 30 minutes. To account for all instances, for each instance, it was computed the percentage changed in Travel Time or Continuity of Care compared to the value obtained when the maximum working time difference allowed is 30 minutes ($\delta = 15$), as suggested by the HHU. Then, the average change for all instances was calculated and can be seen on the vertical axis of the graphs.

Observing first the graph on the left, related to the Travel Time, the reference value is the maximum difference of 30 minutes. When this value decreases to 10 minutes, the Travel Time increases, on average, 4%. By contrast, when this value increases for 40 minutes or 60 minutes, the decrease in Travel Time is almost negligible. Thus, by increasing δ and giving more flexibility to the model to achieve lower Travel Times, it does not significantly improve the Travel Time objective after a maximum difference of 30 minutes (being this the value chosen by the HHU). Even so, one can conclude that Travel Time is slightly influenced by δ. On the other hand, looking for the graph related to the Continuity of Care on the right side, it is possible to conclude that the Continuity of Care is not being influenced by δ.

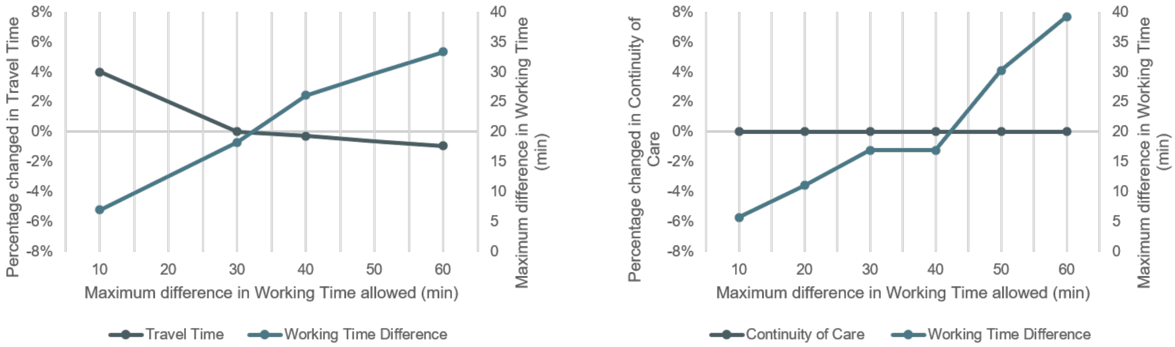


Figure 5.3: Impact of the maximum working time difference allowed in Travel Time (graph on the left) and Continuity of Care (graph on the right)

5.1.2 Solution Approach Illustration

The solution approach presented in section 4.4 was implemented in the real-world instances provided by HGO. In this subsection, instance 16.12 was used to illustrate the application of the solution approach. Firstly, the ϵ-constraint method was applied to find the Pareto front. Then, to reduce the number of non-dominated solutions on the Pareto front, the crowding distance method was used. Lastly, to decide only on one solution from the Pareto front, TOPSIS was used.

The results of the solution approach applied to all the real-world instances are detailed in Appendix B. Table B.5 shows the detailed results of the ϵ-constraint method, Table B.6 for the crowding distance metric (only for instances with more than four non-dominated solutions in the Pareto front), and Table B.7 for TOPSIS.

ϵ-constraint method

Algorithm 1 presented in subsection 4.4.2, which describes the procedure to find the Pareto front, was adapted for the specific case of our model. Firstly, the second objective, namely Continuity of Care, was set to its symmetric to deal with a minimization problem from both objectives and facilitate the interpretation of the results. Then, the Ideal values from both objectives are calculated ($z_1^I = 174.45^*$ and $z_2^I = -38$). Note that the Ideal value for objective function 1 is an Ideal approximate value since it was not possible to obtain a gap of 0% with a computation time of one hour (an * indicates an approximately optimal value). Then, fixing the Ideal values in each of the objectives, the other objective is optimized to obtain the Nadir values. However, CPLEX could not find a solution for the Nadir value of objective function 2 within a computation time limit of one hour. Thus, only the Nadir point of objective function 1 is found ($z_1^N = 203.4^*$).

For this reason, the first point to be added to the Pareto front in step 3 corresponds to the Ideal value of objective function 2 and the Nadir value of objective function 1 ($z_1^N = 203.4^*; z_2^I = -38$). Since the Continuity of Care objective only takes integer values, this was the objective function chosen to set as a constraint since we know how to change ϵ - the variation can be set to be 1. Thus, $\epsilon_2 = -38 + 1 = -37$. The $P_1(\epsilon_2)$ problem is solved again, thus minimizing $f_1(\vec{x})$ subject to $f_2(\vec{x}) \leq -37$. The second solution to be added to the Pareto front is $z_1^* = 190.43^*$ and $z_2^* = -37$.

Continuing with the procedure presented on Algorithm 1, it is possible to obtained the final approximated Pareto front, which can be seen in Figure 5.4 (all the solutions are also presented in Table 5.2). The last solution (solution 7) is the one that gives the approximate Ideal of objective 1 found in the beginning. Thus, it is possible to retrieve an approximate Nadir value of objective function 2 ($z_2^N = -30$). The shape of the Pareto front shows the inherent trade-off and conflict between the two objectives. In fact, to improve one objective, the other needs to be sacrificed.

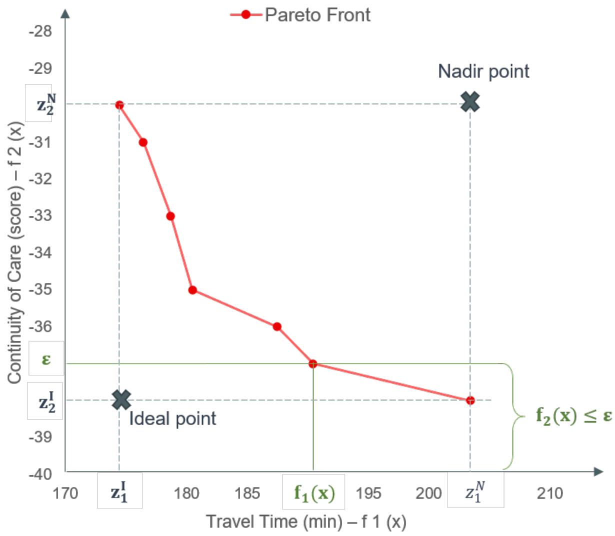


Figure 5.4: Illustration of the Pareto front for instance 16.12

	Objective 1		Objective 2	
Solutions	**TT***	**∆Opt. 1**	**|CC|**	**∆Opt. 2**
1	203.40	16.60%	38	0.00%
2	190.43	9.16%	37	- 2.63%
3	187.50	7.48%	36	- 5.26%
4	180.48	3.46%	35	- 7.89%
5	178.70	2.44%	33	- 13.16%
6	176.43	1.14%	31	- 18.42%
7	174.45	0.00%	30	- 21.05%
Ideal	**174.45**	0.00%	**38**	0.00%
Nadir	203.40	16.60%	30	- 21.05%

TT* represents an approximate Pareto optimal solution since a gap of 0% was not achieved.

Table 5.2: Summary of the non-dominated solutions for instance 16.12

In Table 5.2, the columns $\Delta Opt1$ and $\Delta Opt2$ represent the variation of the solution, in percentage, from the optimum value of objective 1 and 2, respectively. When the Travel Time value decreases to approach the Ideal value, the symmetric value of the Continuity of Care increases (which means that the Continuity of Care is decreasing). The maximum Continuity of Care can be achieved by an increase of 16.6% in Travel Time, which, in this case, represents an increase of around 30 minutes in driving. By contrast, the minimum Travel Time can be achieved by a penalization of 21.05% in Continuity of Care. In conclusion, there is a trade-off between the two objectives, and the final decision on how much we can penalize the Travel Time to increase the Continuity of Care remains to the decision-maker. Nevertheless, this trade-off analysis can bring more value to the decision-maker instead of looking only at a single score provided by a weighted sum.

Crowding distance

Starting from the Pareto front found using the ϵ-constraint method and using again the instance 16.12, the crowding distance metric is applied to find a smaller set of uniformly distributed solutions. The initial Pareto front has seven different non-dominated solutions, as seen in the previous section. It would be possible to present these seven solutions to the decision-maker and leave the final choice to him/her. Nevertheless, it may be challenging to choose between a high number of options. For this reason, the crowding distance values for the intermediate solutions were computed to obtain a reduced and diverse number of solutions.

After following Algorithm 2 presented in subsection 4.4.3, the crowding distance values and the ranking of the options can be seen in Table 5.3. According to the crowding distance method, the boundary solutions are always chosen for the final Pareto front. Then, we can decide to provide one or more solutions to the decision-maker. In this case, the first four best solutions were chosen, which includes the two boundary solutions and two intermediate solutions with the highest crowding distance value, as it is possible to see in Figure 5.5. For solutions in the same Pareto front, a solution with a larger crowding distance is preferred since the objective is to obtain a set of solutions uniformly spread along with the Pareto front (Fu, Wen, 2017). Thus, the final solutions have higher diversity. It is possible to observe from Figure 5.5 that the chosen solutions - marked with a red cross; indeed are well distributed in the Pareto front.

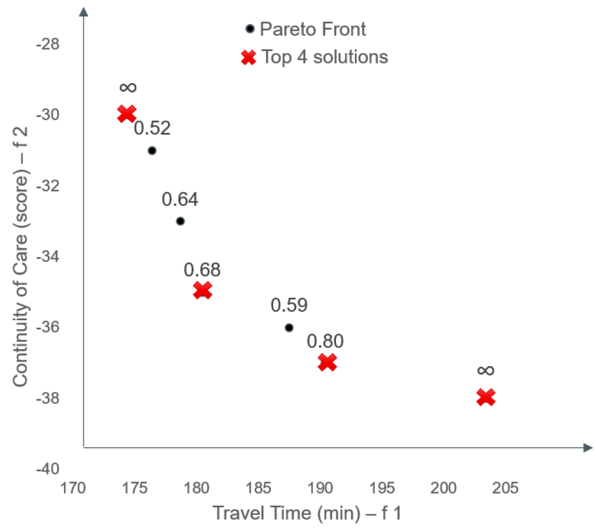


Figure 5.5: Illustration of the Pareto front highlighting the best four ranking solutions

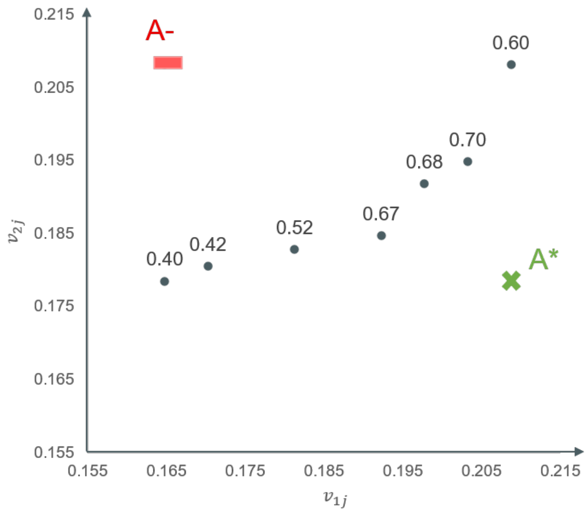
Ranking	CC	TT	Δ_P
1	38	203.40	∞
1	30	174.45	∞
3	37	190.43	0.80
4	35	180.48	0.68
5	33	178.70	0.64
6	36	187.50	0.59
7	31	176.43	0.52

Table 5.3: Ranking of the solutions according to the crowding distance metric

Note that the crowding distance does not require any initial information or input from the decision-maker to be computed. After having the four solutions, the decision-maker can decide if he/she would prefer, for instance, the solution with the lower Travel Time (CC=30; TT=174.45) or increase the Travel Time 3.46% or 9.16% and opt for a solution with more 16.67% or 23.33% of Continuity of Care (respectively solutions (CC=35; TT=180.48) and (CC=37; TT=190.43)). Additional MCDMs could be incorporated to help the decision-maker arrive at the final solution.

TOPSIS

As mentioned before, one technique that can be used in MCDM is TOPSIS. Starting again from the Pareto front found using the ϵ-constraint method, Algorithm 3 presented in subsection 4.4.4 was applied to compute the relative closeness of each alternative. Figure 5.6 shows the seven non-dominated solutions in the vector normalized space, as well as the "ideal" and "negative-ideal" solutions. Table 5.4 shows the solutions ranked according to its relative closeness to the "ideal" solution. By observing Figure 5.6, one can conclude that the three best-ranked options are indeed the ones closer to the ideal solution.



Ranking	CC	TT	C_j^*
1	37	190.43	0.70
2	36	187.50	0.68
3	35	180.48	0.67
4	38	203.40	0.60
5	33	178.70	0.52
6	31	176.43	0.42
7	30	174.45	0.40

Figure 5.6: Mapping of the non-dominated solution in the vector normalized space

Table 5.4: Ranking of the solutions according to TOPSIS

The weights used were 1/2 for each criterion since it was not possible to discuss this further with the decision-maker. For these weights, the best solution is (CC=37; TT=190.43), which was as well the best-ranked intermediate solution according to the crowding distance method. Nevertheless, a sensitivity analysis was performed to understand the importance of determining the weights in this method.

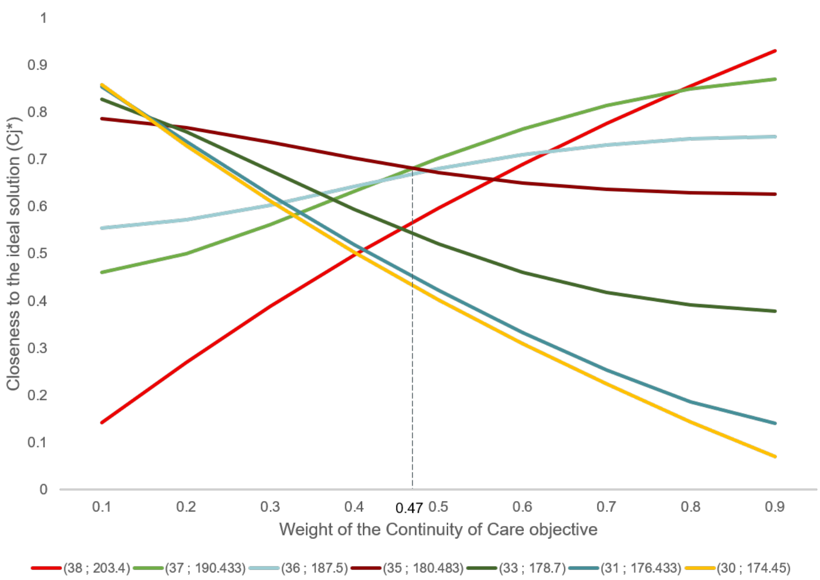


Figure 5.7: Sensitivity analysis for the weights used in TOPSIS

Looking at Figure 5.7 (see Table B.8 in the appendix for the exact values), it is possible to see that the previous solution is the best when the weight of the Continuity of Care objective is within the interval of [0.47-0.78]. If the decision-maker decides that the Travel Time criteria have higher importance than the Continuity of Care, the best solution would be (CC=35; TT=180.48) for a weight of Continuity of Care within [0.19-0.46]. Note that this solution was the second-best intermediate solution according to the crowding distance method as well. The interval for which solution (CC=37; TT=190.43) is the best is slightly larger. In conclusion, this could be an alternative to help the decision-maker to reach a final decision since from here it is possible to have two final solutions, one that values more the Travel Time (CC=35; TT=180.48) and the other which values more the Continuity of Care (CC=37; TT=190.43). Nevertheless, once again, the final decision always remains to the decision-maker.

5.1.3 HGO case study

In this section, the results of the numerical experiments performed in all the real instances are presented. The solution approach illustrated in the previous subsection was followed for the seven instances (seven days from 13/12 to 19/12) and compared with the hospital's results. Table 5.5 shows the results for the computed Pareto fronts (see Table B.5 for the detailed data). Column Time shows the total computation time in seconds for each instance, including finding the Ideal and Nadir values of each objective function and the computation of the ϵ-constraint subproblems. The next column represents the Pareto front size or, in other words, the number of non-dominated solutions found for each instance. Column $P_i(\epsilon_j)$ solved shows the number of ϵ-constraint subproblems solved to arrive at the final Pareto front. The two last columns show, respectively, the average computation time in seconds of the subproblems and the average gap, since a time limit of 3600 seconds was imposed. Thus, it is not possible to prove the optimality in all the subproblems run. Appendix B shows the detailed results for each instance.

Instance	Number of Patients	Total Comp. Time (h)	Pareto front size	Number of $P_i(\epsilon_j)$ solved	Avg. comp. Time of $P_i(\epsilon_j)$ (s)	Avg. Gap $P_i(\epsilon_j)$ (%)
13.12	18	6.72	3	4	3 600.00	15.38
14.12	17	1.00	1	0	-	-
15.12	18	5.28	3	3	2 733.49	9.12
16.12	18	11.00	7	8	3 600.00	12.22
17.12	14	2.28	3	1	733.81	0
18.12	14	5.63	4	6	1 620.14	0
19.12	13	0.26	1	0	-	-
Average		**4.60**	**3**	**3**	**2 457.49**	**7.34**

Table 5.5: Computational Results for the real instances

On average, each instance took 4.6 hours to solve through the ϵ-constraint method. More flexible models, depending on characteristics such as the Travel Time matrix, number of patients, and Continuity of Care score, allow for a higher number of possible solutions. Thus, more subproblems need to be solved, and the computation time increases as well.

Table 5.6 shows the results of the current solution of the hospital and the results obtained by the model focusing on the two objectives that are being optimized, namely Travel Time and Continuity of Care, and on Workload Balance which, even though is not considered as an objective, is a feature that the HHU would like to have considered as well. The final solutions chosen for the model were given by TOPSIS and considering the weight of 1/2 for each objective. By observing the Tables B.6 and B.7 in Appendix B it is possible to conclude that the best solution provided by the TOPSIS method was also the best solution (for instances 16.12 and 18.12) given by the crowding distance (except for the boundary solutions that are automatically chosen by the crowding distance method), thus strengthening the choice of the best solution. It should be noted that the crowding distance metric is only possible to compute when the Pareto front has four or more non-dominated solutions. For this reason, it was only computed for instances 16.12 and 18.12.

	Travel Time (min)			Continuity of Care (score)			Workload Difference (min)		
Instance	Current Solution	Model Solution	Variation (%)	Current Solution	Model Solution	Variation (%)	Current Solution	Model Solution	Variation (%)
13.12	193.27	184.80	**-4.38**	29	30	**+3.45**	29.35	26.07	**-11.19**
14.12	177.38	172.18	**-2.93**	18	18	**0.00**	96.5	15.12	**-84.33**
15.12	186.60	181.65	**-2.65**	31	33	**+6.45**	105.47	27.52	**-73.91**
16.12	187.37	190.43	**1.64**	23	37	**+60.87**	35.85	12.87	**-64.11**
17.12	166.40	150.63	**-9.48**	18	29	**+61.11**	117.62	17.37	**-85.23**
18.12	197.37	166.40	**-15.69**	17	22	**+29.41**	89.85	14.93	**-83.38**
19.12	170.63	143.13	**-16.12**	20	37	**+85.00**	41.4	17.42	**-57.93**
Average			**-7.09**			**+35.18**			**-65.73**

Table 5.6: Comparison between the current manual solution and the solution given by the model

For the hospital's current solution, the Travel Times were computed using the same Travel Time matrix used to compute the model solution and using the order of the visits provided by the hospital. Each team's workload was computed as for the model solution, adding the Travel Time of each team and the total time of visits duration. The highlighted columns show the variation from the current manual solution to the model solution. Note that Workload Balance is measured as the difference between the team which works more in a day and the team which works less. The lower the difference, the better is the Workload Balance. According to Table 5.6, the proposed approach improves the current hospital solutions in both objectives, Travel Time and Continuity of Care, and Workload Balance, except for instance 16.12, where the Travel Time increases 1.64% concerning the current solution. The results show, on average, a reduction in Travel Time of 7.09%. Nevertheless, this small improvement was accompanied by an average increase of 35.18% in Continuity of Care and an average decrease in working time difference within teams of 65.73%. Figure 5.8 illustrates the percentages of improvement of each instance compared to the current manual solution. The graph on the left side is only related to the two objective functions Travel Time and Continuity of Care, while the graph on the right side shows the cumulative improvement of the two objectives and the Workload Balance. For detailed information on the results, refer to Table B.9 in the Appendix B.

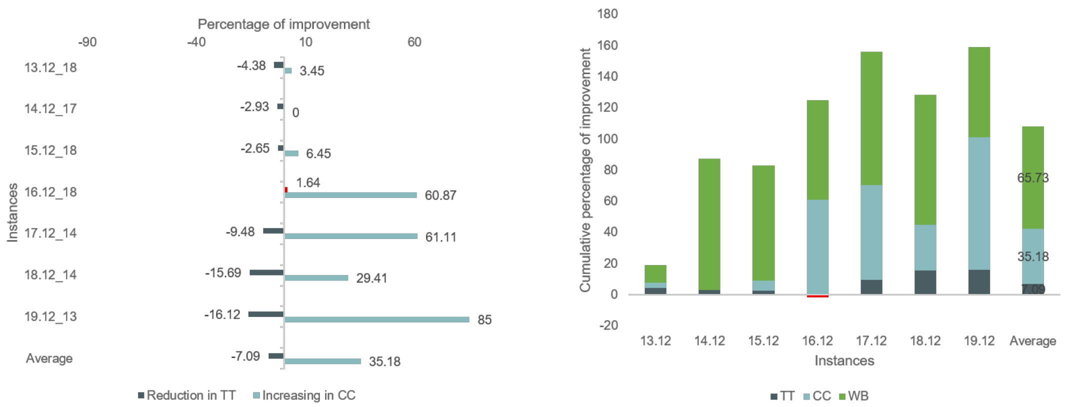


Figure 5.8: Percentage (graph on the left) and Cumulative percentage (graph on the right) of improvement of the model compared to the manual solution

In Table B.11 of Appendix B, it is possible to see, on each day, which patient (represented by numbers) was assigned to which nurse (represented by letters) for the HGO current solution and the model solution. Additionally, the table shows the Continuity of Care score between each pair of patient-nurse before the assignment. The red letters highlight when a patient was not assigned to the nurse with the highest Continuity of Care score available on that day. For the model solution, the patients are assigned to the nurse whom they have the highest Continuity of Care relation 94.64% of the times, while for the current solution, this happens 79.46%. Additionally, on the model solution, for the same patient, it does not happen more than once to be assigned to a nurse who is not the nurse with the highest Continuity of Care score. On the other hand, on the current manual solution, there are patients penalized four times in a period of one week. Note that, for the current solution and model solution, the Continuity of Care scores are different (except for the first instance where the scores started with the same values) since the scores were calculated according to the solution on the previous day given by the current and model solution, respectively. For this reason, as we run the model on successive days, the improvement in Continuity of Care is more evident.

Concerning Workload Balance, the results are illustrated in Figure 5.9 (detailed data on Table B.10). The graphs show the distribution of working time for both solutions in each instance. It is possible to conclude that the working time is better distributed among the different nurses in the model solution than on the HGO solution. For example, on day 17.12, nurse D (in light blue) works less time than nurse E (in dark blue) (nurse A works 3 hours and 24 minutes, nurse D works 3 hours and 22 minutes while nurse E works 5 hours and 20 minutes), whereas that difference is not that evident in the model solution (nurse A works 3 hours and 48 minutes, nurse D works and 4 hours and 5 minutes and nurse E works 3 hours and 58 minutes). Additionally, for each nurse, the average working time at the end of the 7 days was computed. For the manual solution, the standard deviation of the averages is 42 minutes, while for the model solution, it is 27 minutes. By reducing the Travel Time, the teams' total working time also decreases since travel is being done more efficiently. For this reason, the total working time at the end of the 7 days was slightly higher in the manual solution (95.07h) than for the model solution (93.57h). Moreover, by improving Continuity of Care, it is expected that the duration of the service in each patient may decrease as well since nurses are more aware of the patients' status. Thus, the total working time may decrease even more.

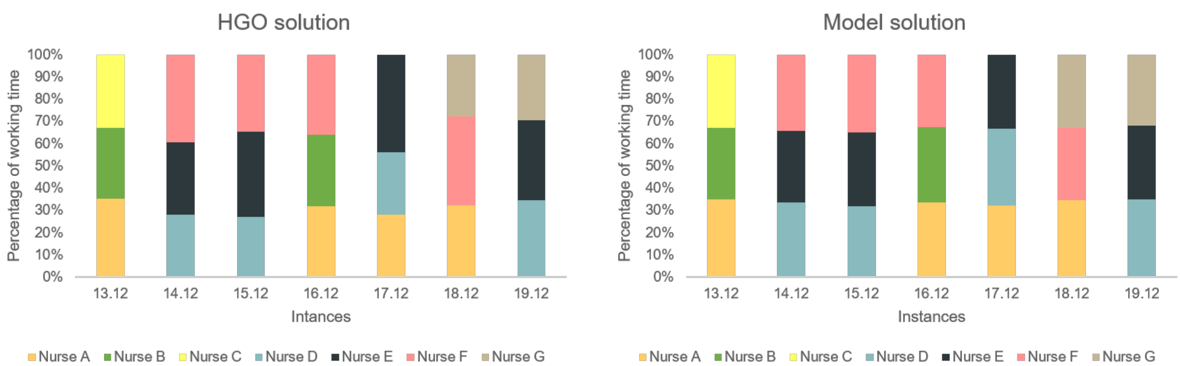


Figure 5.9: Workload Balance within nurses - comparison between the current HGO solution and the model solution

To sum up, on average, the model was able to improve Travel Time by 7.09%. Even though this improvement may not seem significant, at the end of a week, it represents a decrease of 90 minutes of driving time, which will also lead to a reduction in costs. Additionally, it was possible to significantly improve the remaining objectives without compromising the Travel Time (except for instance 16.12). Nevertheless, the solutions given by the model are obtained using weights of 1/2 for each of the objectives. Thus, by changing the weights according to the decision-maker's preferences, it could be possible to obtain solutions that improve even more the decision-maker's preferred criteria.

Furthermore, it is possible to verify what was previously mentioned: HHC institutions sometimes end up focusing more on the management side, leaving the remaining stakeholders - patients and nurses - more prejudiced. From these results, one can conclude that it is possible to improve Travel Time and, consequently, costs while enhancing Continuity of Care and Workload Balance. Therefore, using the proposed model and approach solution could considerably improve all objectives and all stakeholders' perspectives.

5.2 Literature instances

This section shows the application of the model in the literature instances. Subsection 5.2.1 details the instances used and the diverse parameters, while subsection 5.2.2 describes the model's computational performance on the respective instances.

5.2.1 Instances Description

In the field of HHC, there are not many benchmark instances available, especially considering the Continuity of Care feature. The only instances available in the literature with Continuity of Care data were published by Grenouilleau et al. (2019) and can be consulted in `https://doi.org/10.17632/cbgt59hnhk.1`.

The benchmark instances provided by Grenouilleau et al. (2019) contain 60 instances split into 3 sets of 20 instances: Small, with 40 patients and 5 care workers; Medium, with 80 patients and 10 care workers; Large, with 150 patients and 20 care workers. Nevertheless, these instances are provided to solve the HHCRSP for a weekly period, and not a single a day, which means that each instance can originate 7 instances for our daily problem. For each patient, the following information is provided: a location id, the number of required visits during the week, the duration of the service, a list of the available days for visits during the week, time windows per available day, and optional and mandatory skills required by the care workers. To generate daily instances, the patients' available days were mapped, and the number of required visits was ignored to consider instead that the patients must be visited in all the available days. From here, for each day, it was possible to retrieve one instance for the daily problem. The time windows and optional skills were not considered in our case. Nevertheless, the duration of the service and the mandatory skills were used as stated in the instances.

Concerning the care workers, the location id, skills, minimal and maximal work time over the week, workdays, and available time windows were provided. Due to the characteristics of the problem studied in this work, only skills were considered. Additionally, all care workers were considered available to work in each instance, ignoring their available time windows and workdays. Depending on the number of patients in each instance, a number of caregivers were randomly chosen to provide all the visits within the time window of our problem (9 am to 3 pm). The number of caregivers used was based on the hospital information of 3 nurses per 18 patients. For example, for an instance with 18 patients, 3 nurses were randomly chosen out of the 5 available. Additionally, as in our problem there is only one depot, namely the hospital; within the 3 nurses chosen, one location was randomly generated to be the hospital's location and point of departure of all the nurses.

As stated before, the instances contain Continuity of Care scores associated with each patient-caregiver pair, which corresponds to the number of times the caregiver has been assigned to the patient's past visits. Location, distance, maximal speed, and duration between each location are provided. Additionally, traffic indexes between locations are available. From this information, only locations and the duration between each location were used.

The remaining parameters were generated based on data and information provided by HGO. For a reference of 3 nurses and 18 patients, there is, in general, between 2 and 3 patients needing a first-visit, between 2 and 3 patients living in a traffic morning area, and around 4 patients that need to be seen by a physician (if a physician is available). The number of physicians changes between the days and varies between 0 and 3 physicians. The patients with those requirements were generated randomly, and different values (i.e., having 2 patients needing a first-visit or none of them needs a first-visit) were used to understand the impact of the different characteristics.

The Continuity of Care score of the physicians was computed based on the score of the nurses. The nurses' Continuity of Care score ranges from 0 to 4, and for each instance, we calculated the probability of having each score. After that, the probability of having a score of 4 in physicians was considered to be 10% of the probability of a nurse having a score of 4 with the same patient since the number of physicians' visits is usually lower. In the same line, the probability of having a score 3 was considered to be 50% of having the same score for nurses, for score 2, it was considered 30%, and for score 0, it was considered to be 1.3 times more likely for physicians. The remaining probabilities until reaching one (or 100%) were distributed to score 1.

The characteristics of the instances can be found in Table 5.7. The instances were named following the logic CHARACTERISTIC_DATA_NUMBER OF PATIENTS. Each letter on column Data represents a different set of patients, nurses, and physicians. To study the impact of the different parameters on the model, instances with a different number of patients and different data were generated. Moreover, for the same set of data and number of patients, characteristics such as number of first-visits (F), number of patients needing a physician (N), number of skills available (S), number of patients living in areas with heavy traffic (T) and number of physicians available (P) were changed. For example, instance 1_F_14 is composed of 14 patients, using the data set F and the characteristics of what is considered the base instance using data set F. Then instance 2P_F_14 is the second instance using data set F, but this time characteristics P was modified from the base instance.

5.2.2 Experiments

Tests were performed in instances with 14, 16, 18, 22, and 24 patients. There was an attempt to conduct tests in larger instances, but the model could not provide a solution within the time limit of one hour for

Instances	Data	Number of Patients	Number of Nurses	Number of Skills	Number of First-visit	Number of Traffic	Number of Physicians	Need for physician	Break
1_F_14	F	14	3	3	3	3	2	3	yes
2P_F_14	F	14	3	3	3	3	0	0	yes
1_G_16	G	16	3	4	3	3	2	4	yes
2N_G_16	G	16	3	4	3	3	2	6	yes
1_A_18	A	18	3	4	3	3	2	4	yes
2S_A_18	A	18	3	0	3	3	2	4	yes
3N_A_18	A	18	3	4	3	3	2	8	yes
1_B_18	B	18	3	4	3	3	2	4	yes
2F_B_18	B	18	3	4	1	3	2	4	yes
3T_B_18	B	18	3	4	3	0	2	4	yes
1_C_18	C	18	3	4	3	3	2	4	yes
2P_C_18	C	18	3	4	3	3	3	0	yes
1_D_22	D	22	4	4	4	4	3	8	yes
2FT_D_22	D	22	4	4	0	0	3	8	yes
1_E_24	E	24	5	4	5	5	4	14	yes

Table 5.7: Characteristics of the instances

instances with 26 and more patients. The time limit of one hour was imposed for each intermediate run, i.e., to find the Ideal and Nadir values, and for each of the ϵ-constraint subproblems. To explore all the Pareto front, not all the values for Continuity of Care were used. The variation would depend on the solution given. For example, if the subproblem enforces that the Continuity of Care must be greater than or equal to 65, and the result is 71, the next subproblem would enforce the Continuity of Care to be greater than or equal to 71. Note that it was not always possible to obtain a gap of 0%, meaning that the final result is not a Pareto front but an approximate Pareto front. The results of the instances can be found in Table 5.8. Additionally, Table B.12 on Appendix B shows the detailed results of the ϵ-constraint method applied to these instances.

Instances	Total Time (h)	Ideal* TT Time (s)	Ideal* TT Gap (%)	Ideal* CC Time (s)	Ideal* CC Gap (%)	Nadir* TT Time (s)	Nadir* TT Gap (%)	Nadir* CC Time (s)	Nadir* CC Gap (%)	Pareto Size	N of Sub problems	Avg. Comp. time (s)	Average Gap (%)
1_F_14	0.20	76.55	0	141.27	0	205.54	0	101.44	0	4	2	105.81	0
2P_F_14	0.15	98.29	0	161.96	0	48.17	0	55.34	0	4	2	95.76	0
1_G_16	6.41	128.91	0	3600	16.67	3600	No sol.	1520.15	0	6	6	2373.11	4.89
2N_G_16	5.94	134.95	0	3600	0	3600	0	135.22	0	4	5	2201.51	4.63
1_A_18	3.98	346.54	0	3600	No sol.	-	-	322.26	0	4	5	2009.52	0.78
2S_A_18	8.39	267.54	0	3600	3.13	155.23	0	254.29	0	19	19	1364.63	0.31
3N_A_18	1.60	238.15	0	3600	3.33	92.61	0	449.51	0	2	2	683.95	0
1_B_18	1.51	3600	2.06	25.26	0	42.89	0	1679.38	0	3	2	40.48	0
2F_B_18	3.55	3600	7.86	593.42	0	45.26	0	3600	No sol.	5	5	988.81	1.35
3T_B_18	1.66	3600	3.76	81.12	0	11.53	0	1854.57	0	5	4	106.04	0
1_C_18	4.31	99.83	0	3600	No sol.	-	-	388.69	0	4	5	2282.12	0.33
2P_C_18	3.15	359.14	0	3600	No sol.	-	-	888.92	0	2	3	2169.73	0
1_D_22	6.00	3600	12.02	3600	35.38	3600	13.61	3600	No sol.	2	2	3600	9.16
2FT_D_22	20.00	3600	12.24	3600	18.42	3600	14.48	3600	No sol.	10	16	3600	14.54
1_E_24	19.00	3600	18.04	3600	12.24	3600	7.57	3600	No sol.	9	15	3600	13.75

Table 5.8: Computational results for approximate Pareto fronts (the symbol * is used to show that some obtained values can be approximate values)

Graph 5.10 shows the evolution of the total computation time (including the time to find the Ideal and Nadir solutions for both objectives and to find all the Pareto front), with the number of patients. Even though the instances with different patients correspond to different data (making it difficult to make a direct comparison), it is possible to understand that the computation time increases exponentially with the number of patients. As was concluded before, the complexity of the Travel Time matrix influences the computation time.

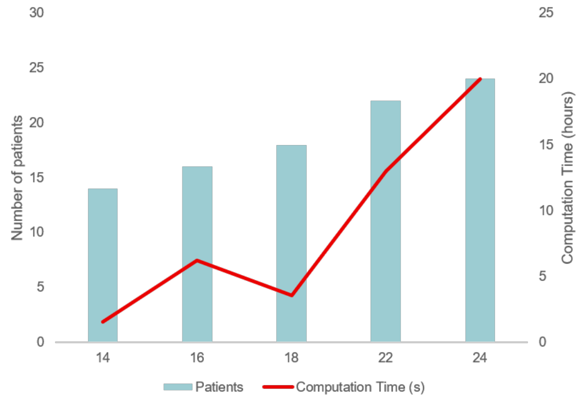


Figure 5.10: Evolution of the computational time (hours) with the number of patients

The first difference one can note compared to the real instances' results is that until 18 patients, the optimization of Travel Time can happen within 400 seconds, except for instances with data set B. This is due to the fact that now all the features of the model are being considered, which may facilitate the assignment and routing process by limiting the number of possible solutions (e.g., first visits and physician requirements). By contrast, when optimizing the Continuity of Care objective, in general, it is not possible to arrive at a gap of 0% within 3600 seconds. In real instances, the model could find the optimal value of Continuity of Care. However, there are more restrictions to respect in the literature instances, and, thus, it is harder to optimize the Continuity of Care.

The instances were defined in order to help understand the impact of the different parameters used in the model. For example, from instance 1_B_18 to instance 2F_B_18, it changes the number of patients needing a first-visit. The first-visit parameter facilitates the routing process since it restricts the possible solutions as some patients need to be the first ones on the routing solution. For this reason, having fewer patients needing a first-visit increased the computation time from 1.51 hours to 3.55 hours. Similarly, instance 3T_B_18 does not have patients living in a traffic area, which also slightly increased the computation time to 1.66 hours. The impact of these two features together can be seen in instances with data D. From instance 1_D_22 to 2FT_D_22, the number of patients needing a first-visit and living in an area with heavy traffic changed to zero. As a consequence, the total computation time increased from 6 hours to 20 hours. The impact can also be seen in the size of the Pareto front, which increased from 2 to 10 due to the increase in the instances' flexibility.

The impact of considering physicians in the model was also studied using the instances of data F. The difference in computation time does not seem to be significant. Still, these instances only consider 14 patients and the impact may not be evident. By contrast, looking at the data G instances, passing from only 4 patients needing to be seen by a physician to 6, slightly decreased the total computation time from 6.41 hours to 5.94 hours.

Looking now at instance 1_A_18, it was solved in a total computation time of 3.98 hours. The Ideal Travel Time was reached in a computation time of 346.54 seconds and a gap of 0%. The Ideal Continuity of Care value was not possible to compute within the time limit. Thus, it was not possible to calculate the

Nadir value of the Travel Time since no Ideal value of the Continuity of Care was known. Nevertheless, it was possible to calculate the Nadir value of the Continuity of Care associated with the Ideal Travel Time, which was reached in a computation time of 322.26 seconds and a gap of 0%. The ϵ-constraint method was applied starting from the Nadir Value of the Continuity of Care until it is no possible to reach a solution within the computation time limit, which may mean (or not) that we arrived already on the Ideal solution of the Continuity of Care. For the cases where it was possible to achieve an Ideal or approximate Ideal value for the Continuity of Care, the ϵ-constraint method was applied until this value is reached. The number of subproblems solved was 5, with an average computation time of 2,009.52 seconds and an average gap of 0.78%. The final approximated Pareto front found has 4 non-dominated solutions- Figure 5.11 in red.

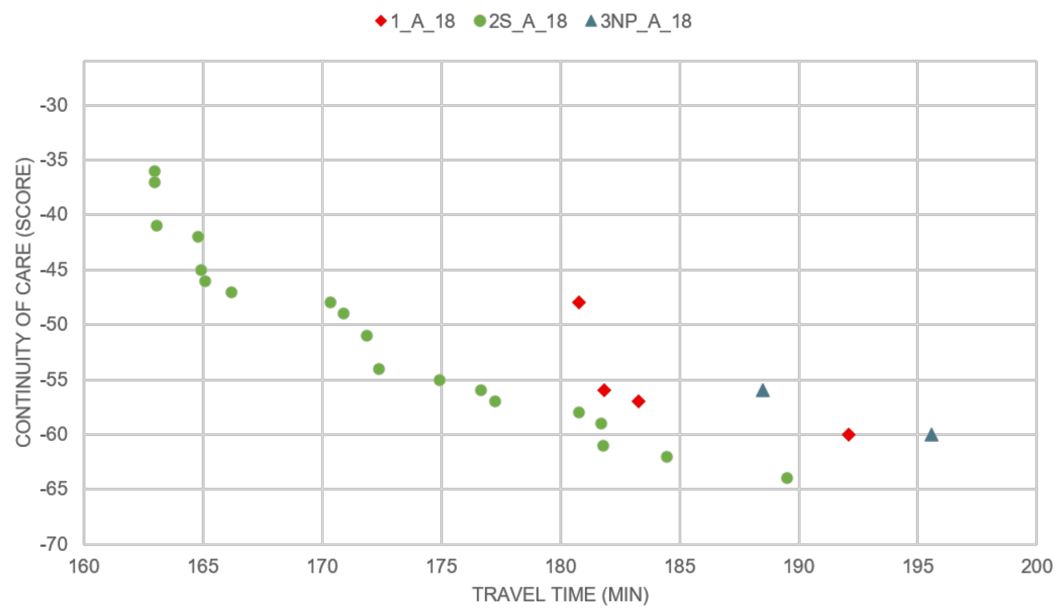


Figure 5.11: Approximate Pareto fronts for three different instances with the same patients, nurses and physicians

Instance 2S_A_18 has the same patients, physicians, and nurses' characteristics identified by letter A. Nevertheless, the nurses' skills and the patients' requirements for those skills were not considered. As a result, the total computational time increased from 3.98 to 8.39 hours, and the approximate Pareto front from 4 to 19 non-dominated solutions - Figure 5.11 in green. This happens because there are more possibilities for assigning patients to nurses, increasing the number of possible non-dominated solutions. In the third instance, 3N_A_18, the number of patients needing a physician rose from 4 to 8. As there are only 2 physicians to assign to the 3 teams, increasing the number of patients who need to be seen by a physician facilitates the assignment process. Thus, the computational time decreased to 1.6 hours, and the exact Pareto front - since the gap was 0% - has only 2 non-dominated solutions - Figure 5.11 in blue. Furthermore, it is also possible to note that more flexible instances allow having better solutions in terms of both objectives since more solutions can be explored. The green curve is closer to the Ideal solution on the bottom left - minimum Travel Time and maximum Continuity of Care - than the remaining curves. From this analysis, it is possible to conclude that the Pareto front's size and structure are highly dependent on the instances' characteristics.

5.3 Chapter conclusions

Numerical experiments were performed in real instances and instances adapted from the literature. The objective of these experiments was to test the applicability of the model to the defined problem and possible improvements in relation to the current manual solution.

The application of the model and solution approach to the real instances allowed an improvement in both objectives simultaneously, and in the feature Workload Balance. On average, the proposed model allowed a reduction in Travel Time of 7.09%, an increase in Continuity of Care of 35.18%, and an increase of 65.73% on Workload Balance.

By improving Travel Time, the costs incurred by the HHU can be decreased when comparing to the current manual solution used by the hospital. Furthermore, it is possible to enhance the Continuity of Care and Workload Balance without compromising the improvement in Travel Time significantly. When analyzing the model from a single-objective perspective, the average improvement on Travel Time was 10.97%, only 3% higher than when considering Continuity of Care and Workload Balance. Nevertheless, it was shown that the Workload Balance could influence the improvement in Travel Time. Similarly, a solution with better Continuity of Care results in a solution with a worst Travel Time. Even so, the HH is a service that cannot ignore stakeholders such as patients and care workers. Thus, the three stakeholders' perspectives can still be improved significantly with the use of this model without compromising Travel Time.

Regarding computational results, the application of the ϵ-constraint method does not always allow to find the exact Pareto front, but an approximate Pareto front. Additionally, the techniques presented to help the decision-maker choose between the Pareto front' solutions, TOPSIS (where a weight of 1/2 was considered for both objectives) and crowding distance, both methods choose the same solution for instances 16.12 and 18.12 (ignoring boundary solutions in the crowding distance method). For this reason, the proposed methods can be used as well together to help in decision making.

The main disadvantage of the presented solution approach and model falls under the computational time. Most of the studied literature uses heuristics to handle the exponential increase in computational time inherent to the VRP. For this reason, heuristic methods should be studied and tested. Some examples of heuristics used in the literature of HHC are VNS, MA and ACO. Another possible approach is to set a smaller time limit for each intermediate run - instead of one hour. Nonetheless, for cases with 26 patients or more, it is not possible to achieve one solution within the time limit of one hour.

Chapter 6

Conclusions and Future Research

Portugal has a significant aged population and has seen in HH an opportunity to decrease hospital congestion. Encouraged by the government to adapt the health care system to the growing needs of an aging population, HH has been expanding rapidly over the last few years. HGO was the first hospital to implement an HHU in Portugal and has already confirmed the unit's benefits. Compared to the conventional ward, the HHU has significant improvements in costs, length of stay, mortality rate, and post-discharge readmission rate. Moreover, it improves the patient's well-being through high levels of personal care and communication with family members. The HGO believes in the innovative character of this patient-centered response and intends to continue to grow the number of patients served and, above all, to improve the quality of service.

To provide high-quality care at the least cost possible, complex logistics and operations decisions need to be considered making it an interesting problem to apply Operations Research techniques. The scheduling and routing tasks are quite complex, and numerous factors must be considered to obtain a feasible solution. The planning is currently done manually by the HGO's HHU, requiring a long time to obtain a valid schedule. Moreover, all these decisions are based on health care professionals' experience with no systematic or decision support.

After a literature review, it was possible to conclude that even though the literature in HHC is quite vast, as far as the author is aware, only one paper in the literature handles the case of an HHU (Quintanilla et al., 2020). There are some characteristics intrinsic to the HH that are not considered in HHC planning, such as having teams composed of nurses and physicians, having patients that need to be seen by a physician due to their status, or patients that need an early morning visit. Moreover, this dissertation addresses the aspect of teams' formation that is not commonly addressed in the HHC literature. Another lack in the literature regards the use of multi-objective functions in order to incorporate the interests of the various stakeholders. The proposed model accounts for the three main stakeholders' perspectives existing in HH: management (Travel Time), patients (Continuity of Care), and care workers (Workload Balance). The Continuity of Care was considered for both nurses and physicians, which was also not found in the literature.

After looking at the results, there is significant room for improvement from the manual solution to the solution provided by the model in the three stakeholders perspectives. Furthermore, it is possible to improve the Travel Time and, consequently, the costs while still improving the Continuity of Care and the Workload Balance. The results show, on average, a reduction in Travel Time of 7.09%. Nevertheless, this small improvement was accompanied by an average increase of 35.18% in Continuity of Care and an average decrease in working time difference within teams of 65.73%. Moreover, in the solution proposed by the model, the patients are assigned to the nurse whom they have the highest Continuity of Care relation 94.64% of the times, while for the current solution, this happens 79.46%. From the workload balance perspective, the standard deviation of each nurse's average working time for the manual solution was 42 minutes, while for the model solution only 27 minutes. Note that the model's solutions are obtained using weights of 1/2 for each of the objectives. Thus, by changing the weights according to the decision-maker's preferences, it could be possible to obtain solutions that improve even more the decision-maker's preferred criteria.

The model also allows providing a comprehensive study of the impact of the different characteristics in the planning. The HGO HHU has emphasized the reduction of travel times and costs. However, it has also shown some concern for the Continuity of Care for patients. Rather than asking them for the importance or weight of each of these objectives, the aim of this dissertation was to analyze the impact of the different objectives. The studied trade-off between Travel Time and Continuity of Care allowed to understand that even though the trade-off exists and it is inventively to improve one objective without compromising the other; it also shows that the impact is not that significant, which means that it is worth it to account for the Continuity of Care and not mainly focus on cost reduction. Being aware of the impact and trade-off of the different perspectives may help in decision-making and resource allocation. Moreover, the proposed solution approach allowed postponing the decision-makers input, which sometimes may be subjective. Only after a high-level of quality information regarding the potential solutions and trade-off, the decision-maker needs to choose one solution.

The main limitation of the proposed model and solution approach is the computation time needed to find all the Pareto front and the fact that the model can only afford small instances. This dissertation contributed to the understanding of the trade-off and parameters used in this problem. Nevertheless, from a practical point o view, a lower computation time may be preferable.

Opportunities for future research should incorporate the study of possible heuristics algorithms to couple with larger instances and find non-dominated solutions within a lower computation time. Furthermore, other variants of the Continuity of Care score may also be studied. For example, the HHU may prefer to privilege the Continuity of Care for patients who have been hospitalized for less time because the patient's condition may not yet be well defined, and ensuring follow-up is crucial. The Continuity of Care score can then also be set according to the length of stay. Additionally, the Continuity of Care score is not easy to interpret, and it should also be thought of as a way to communicate this measure better to the hospital. Online decisions should be studied and proposed. In HH, care workers are faced with real-time information such as a patient who calls for immediate visits. The capability of reacting to these emergencies by determining which care worker is closer to that patient location or immediately available to visit and redefining routes or readjusting the initial plan needs to be incorporated in more robust models.

Bibliography

Akjiratikarl Chananes, Yenradee Pisal, Drake Paul R. PSO-based algorithm for home care worker scheduling in the UK // Computers and Industrial Engineering. 2007. 53, 4. 559–583.

Bashir B., Chabrol M., Caux C. LITERATURE REVIEW IN HOME CARE To cite this version : // 9th International Conference on Modeling, Optimization & SIMulation. 2012. 11.

Bennett Ashlea R., Erera Alan L. Dynamic periodic fixed appointment scheduling for home health // IIE Transactions on Healthcare Systems Engineering. 2011. 1, 1. 6–19.

Bertels Stefan, Fahle Torsten. A hybrid setup for a hybrid scenario: Combining heuristics for the home health care problem // Computers and Operations Research. 2006. 33, 10. 2866–2890.

An Exact ϵ -constraint Method for Bi-objective Combinatorial Optimization Problems - Application to the Traveling Salesman Problem with Profits. // . 2007. February.

Braekers Kris, Hartl Richard F., Parragh Sophie N., Tricoire Fabien. A bi-objective home care scheduling problem: Analyzing the trade-off between costs and client inconvenience // European Journal of Operational Research. 2016. 248, 2. 428–443.

Bredström David, Rönnqvist Mikael. Combined vehicle routing and scheduling with temporal precedence and synchronization constraints // European Journal of Operational Research. 2008. 191, 1. 19–31.

Çakırgil Seray, Yücel Eda, Kuyzu Gültekin. An integrated solution approach for multi-objective, multi-skill workforce scheduling and routing problems // Computers and Operations Research. 2020. 118.

Caplan Gideon A., Sulaiman Nur S., Mangin Dee A., Aimonino Ricauda Nicoletta, Wilson Andrew D., Barclay Louise. A meta-analysis of "hospital in the home". // The Medical journal of Australia. 2012. 197, 9. 512–519.

Cappanera Paola, Scutellà Maria Grazia. Joint assignment, scheduling, and routing models to home care optimization: A pattern-based approach // Transportation Science. 2015. 49, 4. 830–852.

Carello Giuliana, Lanzarone Ettore, Mattia Sara. Trade-off between stakeholders' goals in the home care nurse-to-patient assignment problem // Operations Research for Health Care. 2018. 16. 29–40.

Cheng Eddie, Rich Jennifer Lynn. A Home Health Care Routing and Scheduling Problem 1 Introduction // Natural Scienced and Engineering Council of Canada. 1998. October 1998. 1–16.

Cheng Jennifer, Montalto Michael, Leff Bruce. Hospital at Home // Clinics in Geriatric Medicine. 2009. 25, 1. 79–91.

Cissé Mohamed, Yalçındağ Semih, Kergosien Yannick, Şahin Evren, Lenté Christophe, Matta Andrea. OR problems related to Home Health Care: A review of relevant routing and scheduling problems // Operations Research for Health Care. 2017. 13-14. 1–22.

Deb Kalyanmoy. Multi-objective optimization using evolutionary algorithms. 2001.

Deb Kalyanmoy, Pratap Amrit, Agarwal Sameer, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II // IEEE Transactions on Evolutionary Computation. 2002. 6, 2. 182–197.

Decerle J., Grunder O., Hajjam El Hassani A., Barakat O. A general model for the home health care routing and scheduling problem with route balancing // IFAC-PapersOnLine. 2017. 50, 1. 14662–14667.

Decerle Jérémy, Grunder Olivier, Hajjam El Hassani Amir, Barakat Oussama. A memetic algorithm for a home health care routing and scheduling problem // Operations Research for Health Care. 2018. 16. 59–71.

Decerle Jérémy, Grunder Olivier, Hajjam El Hassani Amir, Barakat Oussama. A hybrid memetic-ant colony optimization algorithm for the home health care problem with time window, synchronization and working time balancing // Swarm and Evolutionary Computation. 2019a. 46, February. 171–183.

Decerle Jérémy, Grunder Olivier, Hajjam El Hassani Amir, Barakat Oussama. A memetic algorithm for multi-objective optimization of the home health care problem // Swarm and Evolutionary Computation. 2019b. 44, September 2018. 712–727.

Demirbilek Mustafa, Branke Juergen, Strauss Arne. Dynamically accepting and scheduling patients for home healthcare // Health Care Management Science. 2019. 22, 1. 140–155.

Di Mascolo Maria, Espinouse Marie Laure, Hajri Zied El. Planning in Home Health Care Structures: A literature review // IFAC-PapersOnLine. 2017. 50, 1. 4654–4659.

Du Gang, Zheng Luyao, Ouyang Xiaoling. Real-time scheduling optimization considering the unexpected events in home health care // Journal of Combinatorial Optimization. 2019. 37, 1.

Eveborn Patrik, Flisberg Patrik, Rönnqvist Mikael. Laps Care-an operational system for staff planning of home care // European Journal of Operational Research. 2006. 171, 3. 962–976.

Fikar Christian, Hirsch Patrick. Home health care routing and scheduling: A review // Computers and Operations Research. 2017. 77. 86–95.

Fu Jianlin, Wen Xian Huan. Model-based multiobjective optimization methods for efficient management of subsurface flow // SPE Journal. 2017. 22, 6. 1984–1998.

Genet Nadine, Boerma Wienke, Kroneman Madelon, Hutchinson Allen, Saltman Richard B. Home Care across Europe - Current structure and future challenges // World Health Organization. 2012. 156.

Gomes Maria Isabel, Ramos Tânia Rodrigues Pereira. Modelling and (re-)planning periodic home social care services with loyalty and non-loyalty features // European Journal of Operational Research. 2019. 277, 1. 284–299.

Gonçalves-Bradley DC, Iliffe S, Doll HA, Broad J, Gladman J, Langhorne P, Richards SH, Sheppard S. Early discharge hospital at home (Review) SUMMARY OF FINDINGS FOR THE MAIN COMPARISON // The Cochrane Collaboration. 2017. 6. 1–134.

Google . Google Maps APIs. 2020.

Grenouilleau Florian, Legrain Antoine, Lahrichi Nadia, Rousseau Louis Martin. A set partitioning heuristic for the home health care routing and scheduling problem // European Journal of Operational Research. 2019. 275, 1. 295–303.

Home Health Care Logistics Management Problems An integrated Approach to support Decisions with Hierarchical Interdependencies. // . 2014. August.

HGO . Unidade De Hospitalização Domiciliária: Programa Funcional 2018. 2018.

HGO . Relatório e Contas de 2018. 2019a.

HGO . Unidade de Hospitalização Domiciliária Indicadores de Atividade. 2019b.

Hertz A., Lahrichi N. A patient assignment algorithm for home care services // Journal of the Operational Research Society. 2009. 60, 4. 481–495.

Hulshof Peter J.H., Kortbeek Nikky, Boucherie Richard J., Hans Erwin W., Bakker Piet J.M. Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS // Health Systems. 2012. 1, 2. 129–175.

Methods for Multiple Attribute Decision Making. // . 1981. 58–191.

INE . Estatísticas da Saúde - 2018. Lisboa: INE, 2020.

Lanzarone Ettore, Matta Andrea. Robust nurse-to-patient assignment in home care services to minimize overtimes under continuity of care // Operations Research for Health Care. 2014. 3, 2. 48–58.

Leff Bruce, Burton Lynda, Mader Scott L., Naughton Bruce, Burl Jeffrey, Inouye Sharon K., Greenough William B., Guido Susan, Langston Christopher, Frick Kevin D., Steinwachs Donald, Burton John R. Hospital at home: Feasibility and outcomes of a program to provide hospital-level care at home for acutely Ill older patients // Annals of Internal Medicine. 2005. 143, 11.

Liu Ming, Yang Dapeng, Su Qiang, Xu Lujun. Bi-objective approaches for home healthcare medical team planning and scheduling problem // Computational and Applied Mathematics. 2018. 37, 4. 4443–4474.

Liu Ran, Yuan Biao, Jiang Zhibin. Mathematical model and exact algorithm for the home care worker scheduling and routing problem with lunch break requirements // International Journal of Production Research. 2017. 55, 2. 558–575.

Mankowska Dorota Slawa, Meisel Frank, Bierwirth Christian. The home health care routing and scheduling problem with interdependent services // Health Care Management Science. 2014. 17, 1. 15–30.

Marcon Eric, Chaabane Sondes, Sallez Yves, Bonte Thérèse. Caregivers routing problem in home health care: Literature review // Studies in Computational Intelligence. 2017. 694. 319–326.

Martin Emilio, Cervantes Alejandro, Saez Yago, Isasi Pedro. IACS-HCSP: Improved ant colony optimization for large-scale home care scheduling problems // Expert Systems with Applications. 2020.

Martinez Clea, Espinouse Marie Laure, Di Mascolo Maria. Continuity of care in home services: A client-centered heuristic for the home health care routing and scheduling problem // 2018 5th International Conference on Control, Decision and Information Technologies, CoDIT 2018. 2018. 1045–1050.

Matta Andrea, Chahed Salma, Sahin Evren, Dallery Yves. Modelling home care organisations from an operations management perspective // Flexible Services and Manufacturing Journal. 2014. 26, 3. 295–319.

Maya Duque P. A., Castro M., Sörensen K., Goos P. Home care service planning. the case of Landelijke Thuiszorg // European Journal of Operational Research. 2015. 243, 1. 292–301.

Milburn Ashlea Bennett, Spicer Jessica. Multi-objective home health nurse routing with remote monitoring devices // International Journal of Planning and Scheduling. 2013. 1, 4. 242.

Ministério da Saúde . Lista de Hospitais públicos com Hospitalização Domiciliária em 2019. 2018.

Nota Explicativa do OE 2020. // . 2020.

The value of coordinated and comprehensive Home Care. // . 1965.

Morris David Evan. Santé Service Bayonne: A French approach to Home Care // Age and Ageing. 1983. 12, 4. 323–328.

Mosquera Federico, Smet Pieter, Vanden Berghe Greet. Flexible home care scheduling // Omega (United Kingdom). 2019. 83. 80–95.

Nickel Stefan, Schröder Michael, Steeg Jörg. Mid-term and short-term planning support for home health care services // European Journal of Operational Research. 2012. 219, 3. 574–587.

OECD . Health at a Glance 2019: OECD Indicators. Paris: OECD Publishing, 2019.

Opricovic Serafim, Tzeng Gwo Hshiung. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS // European Journal of Operational Research. 2004. 156, 2. 445–455.

Park Han Young, Datta-Gupta Akhil, King Michael J. Handling conflicting multiple objectives using Pareto-based evolutionary algorithm during history matching of reservoir performance // Journal of Petroleum Science and Engineering. 2015. 125. 48–66.

Quintanilla Sacramento, Ballestín Francisco, Pérez Ángeles. Mathematical models to improve the current practice in a Home Healthcare Unit. 42, 1. 2020. 43–74.

Rasmussen Matias Sevel, Justesen Tor, Dohn Anders, Larsen Jesper. The Home Care Crew Scheduling Problem: Preference-based visit clustering and temporal dependencies // European Journal of Operational Research. 2012. 219, 3. 598–610.

Rest Klaus Dieter, Trautsamwieser Andrea, Hirsch Patrick. Trends and risks in home health care // Journal of Humanitarian Logistics and Supply Chain Management. 2012. 2, 1. 34–53.

Shepperd Sasha, Doll Helen, Broad Joanna, Gladman John, Iliffe Steve, Langhorne Peter, Richards Suzanne, Martin Finbarr, Harris Roger. Early discharge hospital at home // Cochrane Database of Systematic Reviews. 2009. 1. 1–112.

Shepperd Sasha, Iliffe Steve. Hospital at home versus in-patient hospital care // Cochrane Database of Systematic Reviews. 2005. 3.

Shi Yong, Boudouh Toufik, Grunder Olivier. A hybrid genetic algorithm for a home health care routing problem with time window and fuzzy demand // Expert Systems with Applications. 2017. 72. 160–176.

Shi Yong, Boudouh Toufik, Grunder Olivier, Wang Deyun. Modeling and solving simultaneous delivery and pick-up problem with stochastic travel and service times in home health care // Expert Systems with Applications. 2018. 102. 218–233.

Simões Jorge de Almeida Gonçalo Figueiredo Augusto Inês Fronteira, Hernández-Quevedo Cristina. Health Systems in Transition Portugal // Health Systems in Transition. 2017. 19, 2. 1–184.

Solomon Marius M. Algorithms for the Vehicle Routing and Scheduling Problems With Time Window Constraints. // Operations Research. 1987. 35, 2. 254–265.

Trautsamwieser Andrea, Hirsch Patrick. Optimization of daily scheduling for home health care services // Journal of Applied Operational Research. 2011. 3, 3. 124–136.

Trautsamwieser Andrea, Hirsch Patrick. A Branch-Price-and-Cut approach for solving the medium-term home health care planning problem // Networks. 10 2014. 64, 3. 143–159.

WHO . The Solid Facts - Home Care in Europe. 2008. 36.

Wilson Andrew, Wynn Alison, Parker Hilda. Patient and carer satisfaction with 'Hospital at Home': Quantitative and qualitative results from a randomised controlled trial // British Journal of General Practice. 2002. 52, 474. 9–13.

Wirnitzer Jacqueline, Heckmann Iris, Meyer Anne, Nickel Stefan. Patient-based nurse rostering in home care // Operations Research for Health Care. 2016. 8. 91–102.

Xiao Liyang, Dridi Mahjoub, El Hassani Amir Hajjam. Mathematical Model for the Home Health Care Scheduling and Routing Problem with Flexible Lunch Break Requirements // IFAC-PapersOnLine. 2018. 51, 11. 334–339.

Yalcindag Semih, Matta Andrea, Sahin Evren. Human Resource Scheduling and Routing Problems in Home Health Care Context: A Literature Review // 37th Conference on Operational Research Applied to Health Services (ORAHS). 2012. 1–34.

Yalçındağ Semih, Cappanera Paola, Grazia Scutellà Maria, Şahin Evren, Matta Andrea. Pattern-based decompositions for human resource planning in home health care services // Computers and Operations Research. 2016a. 73. 12–26.

Yalçındağ Semih, Matta Andrea, Şahin Evren, Shanthikumar J. George. The patient assignment problem in home health care: using a data-driven method to estimate the travel times of care givers // Flexible Services and Manufacturing Journal. 2016b. 28, 1-2. 304–335.

Yuan Biao, Liu Ran, Jiang Zhibin. A branch-and-price algorithm for the home health care scheduling and routing problem with stochastic service times and skill requirements // International Journal of Production Research. 2015. 53, 24. 7450–7464.

Yuan Biao, Liu Ran, Jiang Zhibin. Daily scheduling of caregivers with stochastic times // International Journal of Production Research. 2018. 56, 9. 3245–3261.

Appendix A

Mathematical Model

A.1 Model Notation

Sets and indexes

$\mathcal{N}$	Set of patients (nodes) - $\{1, ..., i, ..., j, ..., n\}$
$\mathcal{N}'$	Set of locations including the hospital location $\{0\} - \{0, ..., n\}$
$\mathcal{M}$	Set of medical teams $\{1, ..., m, ...\}$
$\mathcal{P}$	Set of physicians $\{0, ..., p, ...\}$
E	Set of nurses $\{0, ..., e, ...\}$
S	Set of nurses skills $\{0, ..., s, ...\}$

Decision Variables

X_{ijm}	1, if medical team m visits patient j after patient i; 0, otherwise (binary)
S_{im}	Start time of medical team m at patient i (positive real)
Y_{ijm}	1, if team m takes a break between patient i and j visits; 0, otherwise (binary)
B_m	Break time of medical team m (positive real)
Z_{pm}	1, if physician p is assigned to medical team m; 0, otherwise (binary)
Z_{em}	1, if nurse e is assigned to medical team m; 0, otherwise (binary)

Parameters

t_{ij}	Travel Time between patient i and j (positive real)
dur_i	Duration of the visit of patient i (positive real)
K	Big positive real number
startT	Start time of the visits (positive real)
finishT	Maximum finish time of the visits (positive real)
$traffic_i$	1, if patient i lives in a critical region of morning traffic; 0, otherwise (binary)
criticalT	Time until when critical traffic regions cannot be visited (positive real)
breakT	Break duration (positive real)
workBeforeBreak	Time that each team needs to work before taking a break (positive real)

workAfterBreak	Time that each team needs to work after taking a break (positive real)
first$_i$	1, if patient i needs an urgent visit in the morning; 0, otherwise (binary)
q$_i$	1, if patient i needs to be seen by a physician; 0, otherwise (binary)
r$_{is}$	1, if patient i needs to be seen by a nurse with skill s; 0, otherwise (binary)
a$_{es}$	1, if nurse e has skill s; 0, otherwise (binary)
|M|	Number of vehicles available
δ	Acceptable deviation from the ideal average working time (positive real)
CC$_{ip}$	Number of times that physician p has been assigned to patient i (positive real)
CC$_{ie}$	Number of times that nurse e has been assigned to patient i (positive real)

Auxiliary Variables

w$_m$	Workload of team m
u$_m$	Time which team m leaves the hospital
l$_m$	Time which team m returns to the hospital
$\overline{W}$	Average working time for all teams

Table A.1: Sets, Parameters, and Decision Variables

A.2 Model Formulation

Objective Functions

$$Objective\ 1 : min \sum_{m \in M} \sum_{i \in N} \sum_{j \in N'} X_{ijm} \cdot t_{ij}$$

$$Objective\ 2 : max \sum_{p \in P} \sum_{i \in N} \left(CC_{ip} \cdot \sum_{m \in M} \left(\sum_{j \in N'} X_{ijm} \cdot Z_{pm} \right) \right) + \sum_{e \in E} \sum_{i \in N} \left(CC_{ie} \cdot \sum_{m \in M} \left(\sum_{j \in N'} X_{ijm} \cdot Z_{em} \right) \right)$$

Constraints

$$\sum_{m \in M} \sum_{i \in N'} X_{ijm} = 1, \forall j \in N$$

$$\sum_{j \in N} X_{0jm} = \sum_{j \in N} X_{j0m} = 1, \forall m \in M$$

$$\sum_{j \in N'} X_{ijm} = \sum_{j \in N'} X_{jim}, \forall i \in N', m \in M$$

$$\sum_{j\in N'} X_{ijm} \cdot startT + t_{0i} \cdot X_{0im} \leq S_{im} \leq \sum_{j\in N'} X_{ijm} \cdot finishT - t_{i0} \cdot X_{i0m}, \forall i \in N, m \in M$$

$$S_{im} \leq \sum_{j\in N'} X_{ijm} \cdot startT + t_{0i} \cdot X_{0im} + (1 - X_{0im}) \cdot K, \forall i \in N, m \in M$$

$$(S_{im} - criticalT) \cdot traffic_i + (1 - \sum_{j\in N} X_{ijm}) \cdot K \geq 0, \forall i \in N, m \in M$$

$$\sum_{i\in N}\sum_{j\in N} Y_{ijm} = 1, \forall m \in M$$

$$Y_{ijm} \leq X_{ijm}, \forall i, j \in N, m \in M$$

$$S_{im} + dur_i \leq B_m + (1 - \sum_{j\in N} Y_{ijm}) \cdot K, \forall i \in N, m \in M$$

$$B_m + breakT \leq S_{jm} + (1 - \sum_{i\in N} Y_{ijm}) \cdot K, \forall j \in N, m \in M$$

$$startT + workBeforeBreak \leq B_m \leq finishT + workAfterBreak, \forall m \in M$$

$$S_{im} + breakT \cdot Y_{ijm} + (t_{ij} + dur_i) \cdot X_{ijm} \leq S_{jm} + (1 - X_{ijm}) \cdot K, \forall i, j \in N, m \in M$$

$$S_{jm} - (1 - X_{ijm}) \cdot K \leq S_{im} + breakT \cdot Y_{ijm} + (t_{ij} + dur_i) \cdot X_{ijm}, \forall i, j \in N, m \in M$$

$$\sum_{m\in M} Z_{pm} = 1, \forall p \in P$$

$$\sum_{m\in M} Z_{em} = 1, \forall e \in E$$

$$\sum_{p\in P} Z_{pm} \geq 1, \forall m \in M$$

$$\sum_{e\in E} Z_{em} = 1, \forall m \in M$$

$$first_i \leq \sum_{m\in M} X_{0im}, \forall i \in N$$

$$\sum_{j\in N} X_{ijm} \cdot q_i \leq \sum_{p\in P} Z_{pm}, \forall i \in N, m \in M$$

$$\sum_{j\in N'} X_{ijm} \cdot r_{is} \leq \sum_{e\in E} Z_{em} \cdot a_{es}, \forall i \in N, m \in M, s \in S$$

$$S_{im} - t_{0i} + (X_{0im} - 1) \cdot K \leq l_m \leq S_{im} - t_{0i} - (X_{0im} - 1) \cdot K, \forall i \in N, m \in M$$

$$S_{im} + dur_i + t_{i0} + (X_{i0m} - 1) \cdot K \leq u_m \leq S_{im} + dur_i + t_{i0} - (X_{i0m} - 1) \cdot K, \forall i \in N, m \in M$$

$$w_m = u_m - l_m, \forall m \in M$$

$$\overline{W} = \frac{\sum_{m\in M} \times w_m}{|M|}$$

$$\overline{W} - \delta \leq w_m \leq \overline{W} + \delta, \forall m \in M$$

Appendix B

Results

This Appendix presents additional data to complement the Figures and information of Chapter 5.

Table B.1 shows, for the minimization of the Travel Time, the evolution of the gap with the computational time. The different instances were grouped in 17-18 and 13-14 patients to retrieve an average behavior. The same information can be visualized in Figure 5.1.

Instance	13.12	14.12	15.12	16.12		17.12	18.12	19.12	
N of Patients	18	17	18	18		14	14	13	
Time (s)	**Gap (%)**	**Gap (%)**	**Gap (%)**	**Gap (%)**	**Average Gap (17-18 patients)**	**Gap (%)**	**Gap (%)**	**Gap (%)**	**Average Gap (13-14 patients)**
4	31.43	19.04	47.31	49.21	**36.75**	21.54	28.64	17.34	**22.51**
30	19.30	17.10	28.20	27.23	**22.96**	19.27	23.92	10.88	**18.02**
60	15.16	16.78	24.92	21.05	**19.48**	17.81	23.64	10.10	**17.18**
100	15.10	16.77	22.60	15.00	**17.37**	17.20	23.64	8.67	**16.50**
180	15.09	16.65	22.15	14.24	**17.03**	16.43	11.51	7.41	**11.78**
360	14.55	14.31	20.91	13.68	**15.86**	12.78	7.18	5.82	**8.59**
540	14.01	14.03	18.24	13.68	**14.99**	11.93	5.65	4.92	**7.50**
720	13.84	13.80	17.52	13.68	**14.71**	11.34	4.67	4.11	**6.71**
900	13.70	13.65	17.18	13.43	**14.49**	10.82	3.73	2.72	**5.76**
1080	13.22	13.48	15.54	13.43	**13.92**	10.26	0.00	0.00	**3.42**
1260	13.08	13.34	13.60	13.43	**13.36**	9.80	0.00	0.00	**3.27**
1440	13.00	13.23	13.40	13.41	**13.26**	9.31	0.00	0.00	**3.10**
1620	12.91	13.13	13.27	13.33	**13.16**	8.93	0.00	0.00	**2.98**
1800	12.83	13.03	13.14	13.23	**13.06**	8.60	0.00	0.00	**2.87**
1980	12.74	12.95	13.03	13.20	**12.98**	8.31	0.00	0.00	**2.77**
2160	12.64	12.86	12.91	13.11	**12.88**	8.00	0.00	0.00	**2.67**
2340	12.58	12.78	12.14	13.03	**12.63**	7.74	0.00	0.00	**2.58**
2520	12.52	12.70	12.06	12.92	**12.55**	7.50	0.00	0.00	**2.50**
2700	12.46	12.61	11.98	12.86	**12.48**	7.29	0.00	0.00	**2.43**
2880	12.40	12.51	11.90	12.77	**12.40**	7.08	0.00	0.00	**2.36**
3060	12.33	12.46	11.77	12.69	**12.31**	6.86	0.00	0.00	**2.29**
3240	12.28	12.38	11.70	12.62	**12.25**	6.67	0.00	0.00	**2.22**
3420	12.26	12.36	11.67	10.59	**11.72**	6.54	0.00	0.00	**2.18**
3600	12.24	12.78	11.82	10.81	**11.91**	6.96	0.00	0.00	**2.32**

Table B.1: Evolution of the gap with the computation time for the minimization of Travel Time (Data from Figure 5.1)

Table B.2 shows the model and manual solution results when considering the objectives in a single-objective perspective. The percentage of improvement is, on average, 10.72% for the Travel Time objective and 37.11% for the Continuity of Care objective. This table is also illustrated in Figure 5.2.

	Travel Time			Continuity of Care		
Instance	**Manual solution**	**Model solution**	**Improvement (%)**	**Manual solution**	**Model solution**	**Improvement (%)**
13.12	193.27	175.32	**-9.29**	29	30	**3.45**
14.12	177.38	172.18	**-2.93**	18	18	**0.00**
15.12	186.60	177.68	**-4.78**	31	34	**9.68**
16.12	187.37	174.45	**-6.90**	23	38	**65.22**
17.12	166.40	143.85	**-13.55**	18	29	**61.11**
18.12	197.37	154.92	**-21.51**	17	23	**35.29**
19.12	170.63	143.13	**-16.12**	20	37	**85.00**
Average			**-10.72**			**37.11**

Table B.2: Comparison between the model and manual solutions in a single-objective perspective

Table B.3 and Table B.4 complement Figure 5.3. On Table B.4 the minimization of Travel Time and the maximization of Continuity of Care is done for each instance, changing the value of δ (i.e., the acceptable deviation from the average working time) from 5 minutes to 30 minutes. In order to better understand the impact of the Workload balance on both objectives, an average of the instance was considered. For that, the reference value was stated to be δ=15 minutes, and the change on the value of Travel Time or Continuity of Care was measured for each instance when passing to other values of δ. The average change in percentage was considered to build the graphs in Figure 5.3.

Max diff. in WT allowed (min)	Change 15 to 5 (%)	10	Change 15 to 15 (%)	30	Change 15 to 20 (%)	40	Change 15 to 30 (%)	60	10	20	30	40	50	60
δ		5		15		20		30	5	10	15	20	25	30
Instance	**Travel Time**								**Continuity of Care**					
13.12	4.44%	183.10	0%	175.32	-0.64%	174.20	-1.63%	172.47	30	30	30	30	30	30
14.12	0.94%	173.80	0%	172.18	-0.15%	171.93	-1.71%	169.23	18	18	18	18	18	18
15.12	4.94%	186.47	0%	177.68	0.58%	178.72	-1.29%	175.40	34	34	34	34	34	34
16.12	5.18%	185.57	0%	176.43	-1.12%	174.45	-1.12%	174.45	38	38	38	38	38	38
17.12	0.15%	144.07	0%	143.85	-0.48%	143.17	-0.48%	143.17	29	29	29	29	29	29
18.12	5.35%	163.20	0%	154.92	-0.24%	154.55	-0.24%	154.55	22	22	22	22	22	22
19.12	6.86%	152.95	0%	143.13	0.00%	143.13	-0.06%	143.05	37	37	37	37	37	37
Average change to δ=15	**3.98%**		**0.00%**		**-0.29%**		**-0.93%**		**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
Instance	**Working Time Difference**													
13.12		5.65		10.53		35.80		26.72	8.25	15.25	24.48	10.733	38.50	37.93
14.12		8.22		15.12		32.55		35.25	6.15	3.45	13.02	12.300	25.18	50.03
15.12		6.83		28.23		16.45		43.33	6.87	17.67	25.03	16.367	41.25	46.73
16.12		8.10		25.07		15.95		15.95	5.48	16.87	21.57	32.584	23.67	43.15
17.12		3.77		3.77		36.25		36.25	3.60	10.87	8.10	19.534	25.38	21.55
18.12		8.32		27.68		28.05		28.05	3.60	7.07	15.58	20.033	21.60	58.05
19.12		8.22		17.42		17.42		47.73	6.18	6.52	10.82	6.900	35.83	16.85
Average change to δ=15		**7.01**		**18.26**		**26.07**		**33.38**	**5.73**	**11.1**	**16.94**	**16.922**	**30.22**	**39.19**

Table B.3: Impact of δ in the value of the objectives Travel Time and Continuity of Care (Data from Figure 5.3)

	Travel Time				**Continuity of Care**					
Max diff. in WT allowed (min)	10	30	40	60	10	20	30	40	50	60
δ	5	15	20	30	5	10	15	20	25	30
Instance 13.12										
TT	**183.100**	**175.317**	**174.200**	**172.467**	265.483	284.817	287.333	240.483	249.067	277.467
CC	25	26	14	21	**30**	**30**	**30**	**30**	**30**	**30**
WT Team 1 (min)	5.098	5.054	4.696	4.696	5.446	5.477	5.458	5.453	5.226	5.798
WT Team 2 (min)	5.004	4.888	4.997	5.142	5.583	5.622	5.549	5.274	5.184	5.165
WT Team 3 (min)	5.034	5.064	5.293	5.120	5.479	5.731	5.866	5.364	5.825	5.745
Max diff. in WT (min)	**5.650**	**10.533**	**35.800**	**26.717**	**8.250**	**15.250**	**24.483**	**10.733**	**38.500**	**37.933**
Instance 14.12										
TT	**173.800**	**172.183**	**171.933**	**169.233**	251.550	266.150	272.850	265.617	265.200	248.517
CC	5	18	18	15	**18**	**18**	**18**	**18**	**18**	**18**
WT Team 1 (min)	4.658	4.688	4.887	4.887	5.129	5.166	5.354	5.290	5.437	5.210
WT Team 2 (min)	4.634	4.548	4.345	4.800	5.166	5.223	5.138	5.218	5.017	5.466
WT Team 3 (min)	4.771	4.800	4.800	4.300	5.064	5.214	5.222	5.085	5.133	4.632
Max diff. in WT (min)	**8.216**	**15.117**	**32.550**	**35.250**	**6.150**	**3.450**	**13.016**	**12.300**	**25.183**	**50.033**
Instance 15.12										
TT	**186.467**	**177.683**	**178.717**	**175.400**	243.933	233.450	232.733	232.233	223.300	245.067
CC	14	12	15	16	**34**	**34**	**34**	**34**	**34**	**34**
WT Team 1 (min)	5.096	5.299	5.228	4.798	5.453	5.394	5.458	5.384	5.037	5.333
WT Team 2 (min)	5.188	5.084	5.047	4.854	5.374	5.226	5.127	5.081	5.210	5.890
WT Team 3 (min)	5.074	4.828	4.954	5.521	5.489	5.521	5.544	5.656	5.724	5.111
Max diff. in WT (min)	**6.833**	**28.234**	**16.450**	**43.334**	**6.866**	**17.667**	**25.034**	**16.367**	**41.250**	**46.733**
Instance 16.12										
TT	**185.567**	**176.433**	**174.450**	**174.450**	259.967	274.500	267.583	310.867	267.000	262.050
CC	14	12	16	18	**38**	**38**	**38**	**38**	**38**	**38**
WT Team 1 (min)	4.921	5.061	4.855	4.855	5.286	5.513	5.334	5.558	5.280	5.313
WT Team 2 (min)	4.786	4.736	4.643	4.909	5.319	5.331	5.133	5.290	5.532	4.918
WT Team 3 (min)	4.885	4.643	4.909	4.643	5.228	5.231	5.493	5.833	5.138	5.637
Max diff. in WT (min)	**8.100**	**25.067**	**15.950**	**15.952**	**5.483**	**16.867**	**21.567**	**32.584**	**23.666**	**43.150**
Instance 17.12										
TT	**144.067**	**143.850**	**143.167**	**143.167**	166.400	197.367	189.567	208.883	196.867	209.683
CC	5	5	6	11	**29**	**29**	**29**	**29**	**29**	**29**
WT Team 1 (min)	3.943	3.943	4.208	3.604	4.028	4.271	4.168	4.438	4.310	4.427
WT Team 2 (min)	3.911	3.880	3.604	4.208	4.009	4.089	4.230	4.112	3.941	4.068
WT Team 3 (min)	3.880	3.908	3.908	3.908	4.069	4.263	4.095	4.265	4.364	4.333
Max diff. in WT (min)	**3.767**	**3.767**	**36.250**	**36.250**	**3.600**	**10.867**	**8.100**	**19.534**	**25.384**	**21.550**
Instance 18.12										
TT	**163.200**	**154.917**	**154.550**	**154.550**	230.900	219.917	179.317	186.400	193.517	221.967
CC	11	1	6	6	**22**	**22**	**22**	**22**	**22**	**22**
WT Team 1 (min)	3.879	3.704	3.879	3.879	4.299	4.220	3.920	3.957	3.957	4.783
WT Team 2 (min)	3.989	4.165	4.165	4.165	4.357	4.338	4.056	4.026	4.118	3.815
WT Team 3 (min)	4.018	3.879	3.698	3.698	4.359	4.274	4.180	4.291	4.317	4.269
Max diff. in WT (min)	**8.317**	**27.683**	**28.050**	**28.050**	**3.600**	**7.067**	**15.583**	**20.033**	**21.600**	**58.050**
Instance 19.12										
TT	**152.950**	**143.133**	**143.133**	**143.050**	172.667	173.000	164.900	169.700	178.117	159.983
CC	14	6	6	9	**37**	**37**	**37**	**37**	**37**	**37**
WT Team 1 (min)	3.570	3.521	3.521	3.521	3.729	3.729	3.594	3.737	3.457	3.593
WT Team 2 (min)	3.683	3.702	3.702	3.159	3.648	3.648	3.631	3.622	3.708	3.521
WT Team 3 (min)	3.546	3.412	3.412	3.954	3.751	3.756	3.774	3.720	4.054	3.802
Max diff. in WT (min)	**8.217**	**17.417**	**17.417**	**47.734**	**6.183**	**6.517**	**10.817**	**6.900**	**35.834**	**16.850**

Table B.4: Detailed solutions for each objective and each instance, changing δ

	TT (min)	CC (score)	WT 1 (min)	WT 2 (min)	WT 3 (min)	Max. Diff. (min)	GAP (%)	Comp. Time (s)	Best Integer	Best Bound	Nº of solutions	Solution
Instance 13.12												
Min TT	175.32	26	5.05	4.89	5.06	10.53	12.24	3600.00	175.32	153.86	14	C
Max CC	287.33	30	5.46	5.55	5.87	24.48	0.00	9.21	30.00	30	1	Dom. by A
Nadir TT	184.80	30	5.30	4.87	5.00	26.07	0.00	2564.90	184.80	184.78	23	A
Nadir CC				No solution				3600.00				
Min TT st CC=29	184.80	30	5.30	4.87	5.00	26.07	15.43	3600.00	184.80	156.28		A
Min TT st CC=28	186.88	28	5.06	4.88	5.26	22.82	17.64	3600.00	186.88	153.91	37	Dom. by A
Min TT st CC=27	181.55	27	4.85	5.00	5.26	24.55	15.73	3600.00	181.55	152.98	20	B
Min TT st CC=26	175.32	26	5.05	4.89	5.06	10.53	12.69	3600.00	175.32	153.07	38	C
Instance 14.12												
Min TT	172.183	18	4.69	4.55	4.80	15.12	12.78	3600.00	172.18	150.92	7	A
Max CC	272.85	18	5.35	5.14	5.22	13.02	0.00	13.59	18.00	18	1	Dom. by A
Instance 15.12												
Min TT	177.68	12	5.30	5.08	4.83	28.23	11.82	3600.00	177.68	156.68	23	Dom. by C
Max CC	232.73	34	5.46	5.13	5.54	25.03	0.00	14.88	34.00	34	5	Dom. by A
Nadir TT	213.70	34	5.25	5.04	5.52	28.83	17.74	3600.00	213.70	175.78	10	A
Nadir CC				No solution				3600.00				
Min TT st CC=33	186.033	33	4.90	5.11	5.34	26.70	3.03	1000.47	33.00	34	2	Dom. by B
Min TT st CC=32	181.65	33	4.88	5.05	5.34	27.52	13.24	3600.00	181.65	157.60	18	B
Min TT st CC=31	177.283	31	5.19	4.82	5.19	22.05	11.09	3600.00	177.28	157.63	8	C
Instance 16.12												
Min TT	174.45	12	5.06	4.74	4.64	25.07	10.81	3600.00	176.43	157.36	23	Dom. by G
Max CC	267.583	38	5.33	5.13	5.49	21.57	0.00	5.29	38.00	38	3	Dom. by A
Nadir TT	203.40	38	4.94	5.17	4.79	22.83	9.24	3600.00	203.40	184.61	18	A
Nadir CC				No solution				3600.00				
Min TT st CC=37	190.43	37	4.94	4.98	4.76	12.87	9.29	3600.00	190.98	172.75	15	B
Min TT st CC=36	187.50	36	4.78	5.06	4.79	17.02	11.53	3600.00	187.50	165.88	13	C
Min TT st CC=35	180.48	35	4.77	5.06	4.68	23.08	12.04	3600.00	180.48	158.76	27	D
Min TT st CC=34	180.48	35	4.77	5.06	4.68	23.08	14.08	3600.00	180.48	155.07	15	D
Min TT st CC=33	178.70	33	4.77	5.06	4.65	24.20	13.30	3600.00	178.70	154.93	14	E
Min TT st CC=32	178.70	33	4.77	5.06	4.65	24.20	13.28	3600.00	178.70	154.96	21	E
Min TT st CC=31	176.43	31	4.64	5.06	4.74	25.07	12.38	3600.00	176.43	154.16	33	F
Min TT st CC=30	174.45	30	4.64	4.91	4.86	15.95	11.89	3600.00	174.45	153.71	24	G
Instance 17.12												
Min TT	143.85	5	3.94	3.88	3.91	3.77	6.96	3600.00	143.85	133.84	12	Dom. by C
Max CC	189.567	29	4.17	4.23	4.09	8.10	0.00	4.74	29	29	1	Dom. by A
Nadir TT	150.633	29	4.09	3.96	3.80	17.37	0.00	284.80	150.633	150.619	7	A
Nadir CC	143.85	26	3.91	3.88	3.94	3.77	7.69	3600.00	26	28	11	C
Min TT st CC=27	147.717	28	3.94	3.92	3.94	1.58	0.00	733.81	147.717	147.70	9	B
Instance 18.12												
Min TT	154.917	1	3.70	4.17	3.88	27.68	0	1486.16	154.92	154.90	15	Dom. by D
Max CC	222.217	23	4.32	4.09	4.46	22.13	4.35	3600.00	23.00	24	4	Dom. by A
Nadir TT	180.733	23	4.13	4.24	3.81	25.87	0	1861.48	180.73	180.72	22	A
Nadir CC				No solution				3600.00				
Min TT st CC=22	166.40	22	4.13	3.93	3.88	14.93	0	854.98	166.40	166.38	9	B
Min TT st CC=21	166.40	22	4.13	3.88	3.93	14.93	0	2703.80	166.40	166.38	6	B
Min TT st CC=20	158.10	20	4.13	3.98	3.70	25.83	0	600.31	158.10	20	13	C
Min TT st CC=19	158.10	20	4.13	3.98	3.70	25.83	0	1353.43	158.10	158.09	10	C
Min TT st CC=18	158.10	20	4.13	3.70	3.98	25.83	0	2397.70	158.10	158.08	26	C
Min TT st CC=17	154.917	17	3.88	3.70	4.17	27.68	0	1810.63	154.92	154.90	8	D
Instance 19.12												
Min TT	143.133	6	3.52	3.70	3.41	17.42	0	877.04	143.13	143.12	10	Dom. by A
Max CC	171.85	37	3.84	3.55	3.73	17.37	0	46.03	37.00	37	4	Dom. by A
Nadir TT	143.133	37	3.41	3.52	3.70	17.42	0	17.48	143.13	143.13	7	A

TT – Travel Time; CC – Continuity of Care; WT 1 – Working Time of Team 1; Max. Diff. – Maximum Difference in WT between teams; Dom. By – Dominated by

Table B.5: Detailed results of the ϵ-constraint method applied to the real instances

Table B.5 shows the results of the application of the ϵ-constraint method for each instance. Firstly, the Ideal values' solution is presented (Min TT and Max CC), then the solution for the Nadir values (Nadir TT and Nadir CC), and lastly, for the subproblems. The information on this table is also summarized in Table 5.5. Table B.6 shows the crowding distance metric's application to instances 16.12 and 18.12. The table shows the calculation of different variables presented in Algorithm 2. It was not possible to apply the crowding distance metric for the remaining instances since, in those instances, the Pareto front has less than four solutions. Similarly, Table B.7 shows the calculation of variables needed in Algorithm 3 to apply TOPSIS. In this case, TOPSIS was not used on instances 14.12 and 19.12 since a single solution was found during the ϵ-constraint method.

Solution	TT - z_1	Δz_1	d_i^p	$d_i^p / \Delta z_1$	CC - z_2	Δz_2	d_i^p	$d_i^p / \Delta z_2$	Δ_p	Rank
					Instance 16.12					
A	203.40				38				inf	1
B	190.43		15.90	0.55	37		2	0.25	0.80	3
C	187.50		9.95	0.34	36		2	0.25	0.59	6
D	180.48	28.95	8.80	0.30	35	8	3	0.38	0.68	4
E	178.70		4.05	0.14	33		4	0.50	0.64	5
F	176.43		4.25	0.15	31		3	0.38	0.52	7
G	174.45				30				inf	1
					Instance 18.12					
A	180.73				23				INF	1
B	166.40	25.81	22.63	0.88	22	6	3	0.50	1.38	3
C	158.10		11.48	0.44	20		5	0.83	1.28	4
D	154.92				17				INF	1

Table B.6: Application of the Crowding distance metric to all instances

Solution	TT - z_1	CC - z_2	r_{1j}	r_{2j}	v_{1j}j	v_{2j}j	S_j^*	S_j^-	C_j^*	Rank
					Instance 13.12					
A	184.80	30	0.59	0.62	0.30	0.31	0.04	0.02	0.27	3
B	181.55	27	0.58	0.56	0.29	0.28	0.01	0.03	0.74	1
C	175.32	26	0.56	0.54	0.28	0.27	0.02	0.04	0.73	2
					Instance 15.12					
A	213.70	34	0.64	0.60	0.32	0.30	0.05	0.03	0.33	3
B	181.65	33	0.55	0.58	0.27	0.29	0.01	0.05	0.82	1
C	177.28	31	0.53	0.55	0.27	0.27	0.03	0.05	0.67	2
					Instance 16.12					
A	203.40	38	0.42	0.42	0.21	0.21	0.03	0.04	0.60	4
B	190.43	37	0.39	0.41	0.19	0.20	0.02	0.04	0.70	1
C	187.50	36	0.38	0.40	0.19	0.20	0.02	0.04	0.68	2
D	180.48	35	0.37	0.38	0.18	0.19	0.02	0.04	0.67	3
E	178.70	33	0.37	0.36	0.18	0.18	0.03	0.03	0.52	5
F	176.43	31	0.36	0.34	0.18	0.17	0.04	0.03	0.42	6
G	174.45	30	0.36	0.33	0.18	0.16	0.04	0.03	0.40	7
					Instance 17.12					
A	150.63	29	0.45	0.51	0.23	0.26	0.06	0.10	0.62	1
B	147.72	28	0.45	0.49	0.22	0.25	0.07	0.10	0.60	2
C	143.85	26	0.43	0.46	0.22	0.23	0.09	0.11	0.57	3
					Instance 18.12					
A	180.73	23	0.55	0.56	0.27	0.28	0.04	0.07	0.65	2
B	166.40	22	0.50	0.53	0.25	0.27	0.02	0.06	0.75	1
C	158.10	20	0.48	0.48	0.24	0.24	0.04	0.05	0.58	3
D	154.92	17	0.47	0.41	0.23	0.21	0.07	0.04	0.35	4

Table B.7: Results from TOPSIS for all instances

			Weight of the Continuity of Care objective								
		(CC ; TT)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Solutions	1	(38 ; 203.4)	0.142	0.271	0.389	0.497	0.597	0.690	0.776	0.856	0.930
	2	(37 ; 190.433)	0.460	0.500	0.562	0.633	0.702	0.764	0.814	0.849	0.869
	3	(36 ; 187.5)	0.554	0.572	0.603	0.642	0.680	0.710	0.731	0.743	0.749
	4	(35 ; 180.483)	0.786	0.767	0.737	0.702	0.672	0.650	0.637	0.629	0.626
	5	(33 ; 178.7)	0.827	0.759	0.676	0.594	0.520	0.460	0.417	0.391	0.378
	6	(31 ; 176.433)	0.854	0.738	0.625	0.520	0.422	0.333	0.253	0.187	0.141
	7	(30 ; 174.45)	0.858	0.729	0.611	0.503	0.403	0.310	0.224	0.144	0.070

Table B.8: Sensitivity analysis on the weight of Continuity of Care for TOPSIS, highlighting at each weight the best solution (Data from Figure 5.7)

Table B.8 shows the variation of relative closeness (calculated with TOPSIS) of each solution with the weight of Continuity of Care considered while applying TOPSIS. Note that by changing the weight of Continuity of Care from 0.5 to 0.6, the weight of the objective Travel Time changes from 0.5 to 0.4. The highlighted cells show the best solution given by TOPSIS for each weight. The illustration of this table can be seen in Figure 5.7.

	13-Dec		14-Dec		15-Dec		16-Dec		17-Dec		18-Dec		19-Dec	
	Manual	**Model**	**Manual**	**Model**	**Manual**	**Model**	**Manual**	**Model**	**Manual**	**Model**	**Manual**	**Model**	**Manual**	**Model**
Travel Time Team 1	68.08		58.62		58.62		58.52		52.28		65.65		56.65	
Travel Time Team 2	68.73		48.65		59.08		59.00		64.90		53.43		63.05	
Travel Time Team 3	56.45		70.12		68.90		69.85		49.22		78.28		50.93	
Total Travel Time	**193.27**	**184.80**	**177.38**	**172.18**	**186.60**	**181.65**	**187.37**	**190.43**	**166.40**	**150.63**	**197.37**	**166.40**	**170.63**	**143.13**
Continuity of care	**29**	**30**	**18**	**18**	**31**	**33**	**23**	**37**	**18**	**29**	**17**	**22**	**20**	**37**
Total visits duration Team 1	255		180	180	190		225	225	150		175		140	
Total visits duration Team 2	225		225	225	295		220	220	255		155		175	
Total visits duration Team 3	245		265	265	250		245	245	155		220		180	
Work of Team 1	5.38	5.30	3.98	4.69	4.14	4.88	4.73	4.94	3.37	4.09	4.01	4.13	3.28	3.41
Work of Team 2	4.90	4.87	4.56	4.55	5.90	5.05	4.65	4.98	5.33	3.96	3.47	3.93	3.97	3.52
Work of Team 3	5.02	5.00	5.59	4.80	5.31	5.34	5.25	4.76	3.40	3.80	4.97	3.88	3.85	3.70
Max. diff. in Working Time	**29.35**	**26.07**	**96.50**	**15.12**	**105.47**	**27.52**	**35.85**	**12.87**	**117.62**	**17.37**	**89.85**	**14.93**	**41.40**	**17.42**

Variation	13-Dec	14-Dec	15-Dec	16-Dec	17-Dec	18-Dec	19-Dec	Average
Travel Time	-4.38	-2.93	-2.65	1.64	-9.48	-15.69	-16.12	-7.09
Continuity of Care	3.45	0.00	6.45	60.87	61.11	29.41	85.00	35.18
Workload balance	-11.19	-84.33	-73.91	-64.11	-85.23	-83.38	-57.93	-65.73
Cumulative improvement	19.01	87.27	83.01	126.62	155.82	128.48	159.05	108.47

Table B.9: Detailed solutions and comparisons of the current manual solution and the model solution chosen from the TOPSIS method (Data from Table 5.5, Figure 5.6, and Figure 5.8)

Table B.9 shows the solutions chosen for each instance using TOPSIS. Those solutions were used to compare with the current manual solution in terms of Travel Time, Continuity of Care and Workload Balance. The table summarizes the improvements. On Chapter 5. Table 5.5, Figure 5.6, and Figure 5.8 illustrate these data.

		Nurse A	Nurse B	Nurse C	Nurse D	Nurse E	Nurse F	Nurse G
Manual Solution	13.12	5.38	4.90	5.02				
	14.12				3.98	4.56	5.59	
	15.12				4.14	5.90	5.32	
	16.12	4.65	4.73				5.25	
	17.12	3.40			3.37	5.33		
	18.12	4.01					4.97	3.47
	19.12				3.85	3.97		3.28
Average		4.36	4.81	5.02	3.84	4.94	5.28	3.38

Standard Deviation = 42 min

Total working time = 95.07h

		Nurse A	Nurse B	Nurse C	Nurse D	Nurse E	Nurse F	Nurse G
Model Solution	13.12	5.30	4.87	5.00				
	14.12				4.69	4.55	4.80	
	15.12				4.88	5.05	5.34	
	16.12	4.94	4.98				4.76	
	17.12	3.80			4.09	3.96		
	18.12	4.13					3.88	3.93
	19.12				3.70	3.52		3.41
Average		4.54	4.92	5.00	4.34	4.27	4.70	3.67

Standard Deviation = 27 min

Total working time = 93.57h

Table B.10: Comparison between the manual and model solutions on the Nurses' Working Time distribution

Table B.11 and Table B.10 compare the manual and model solution regarding Continuity of Care and Workload Balance, respectively. Table B.11 is discussed in detail in subsection 5.1.3 of Chapter 5. Table B.10 is illustrate through Figure 5.9 and shows the working time of each nurse, on each day for both solutions.

Lastly, Table B.12 shows the detailed results of the ϵ-constraint method applied to each of the literature instances, similarly to Table B.5 on the real instances. Table 5.8 on subsection 5.2.2 shows the summary of these results.

Model solution

	13.12				14.12				15.12				16.12				17.12				18.12				19.12			
	A	B	C		D	E	F		D	E	F		B	A	F		D	E	A		A	G	F		G	E	D	
1	0	0	0	B	0	0	0	E	0	1	0	E	1	0	0	B	0	2	0	E	0	0	0	G	1	3	0	E
2	1	0	0	A																								
3	0	0	0	A	0	0	0	E	0	1	0	E	0	1	0	A	0	2	2	E	2	0	0	A	0	3	0	E
4	0	0	0	A	0	0	0	E	0	1	0	E	0	1	0	A	0	2	2	E	2	0	0	A	0	3	0	E
5	2	0	0	A	0	0	2	F	0	0	3	F	0	3	4	A												
6	3	0	0	A	0	1	2	F	0	1	3	F	0	4	4	A					5	0	4	A	0	1	0	G
7	0	0	0	B	0	0	0	F	0	0	1	F	1	0	2	F	0	0	0	A	1	0	3	F	0	0	0	G
8	0	2	1	B	6	2	0	D	7	2	0	D	3	0	0	B					0	0	0	F	0	2	8	D
9	0	1	0	B																								
10	2	1	2	A	1	2	2	E	1	3	2	F	1	3	3	A	1	3	4	A					0	3	1	E
11	1	1	1	B	0	0	0	D	1	0	0	D	2	1	0	B	2	0	1	D					0	0	3	D
12	0	3	1	B	1	1	0	E	1	2	0	E	4	0	0	B	1	3	0	E	0	0	0	G				
13	0	0	1	C	0	0	0	D	1	0	0	D	0	0	0	F												
14	0	0	0	C	0	0	0	D	1	0	0	D	0	0	0	F	2	0	0	D	0	0	1	G	1	0	3	D
15	0	0	1	C																								
16	1	8	10	C	2	2	0	D	3	2	0	D	8	1	0	B	4	2	1	D	1	0	0	G	1	2	5	D
17	0	0	2	C																								
18	0	0	1	C	3	1	1	D	4	1	1	D	0	0	1	F	5	1	0	D	0	0	2	F	0	1	6	D
19					0	0	0	D	1	0	0	D	0	0	0	B	2	0	0	D	0	0	0	G				
20					0	0	0	F	0	0	1	F	0	0	2	F	0	0	0	A	1	0	3	F	0	0	0	G
21					0	0	0	F	0	0	1	F	0	0	2	F	0	0	0	D	0	0	3	F				
22									0	0	0	E	0	0	0	A	0	1	1	A	2	0	0	A	0	1	0	G

HGO Manual solution

	13.12				14.12				15.12				16.12				17.12				18.12				19.12			
	A	B	C		D	E	F		D	E	F		B	A	F		D	E	A		A	G	F		G	E	D	
1	0	0	0	A	0	0	0	F	0	0	1	F	0	1	1	F	0	0	1	A	2	0	2	F	0	0	0	E
2	1	0	0	A																								
3	0	0	0	A	0	0	0	F	0	0	1	F	0	1	2	F	0	0	1	E	1	0	3	F	0	1	0	E
4	0	0	0	A	0	0	0	F	0	0	1	F	0	1	2	F	0	0	1	E	1	0	3	F	0	1	0	E
5	2	0	0	A	0	0	2	F	0	0	3	F	0	3	4	F												
6	3	0	0	A	0	1	2	F	0	1	3	F	0	4	4	F					4	0	5	F	0	1	0	E
7	0	0	0	B	0	0	0	E	0	1	0	E	1	0	0	B	0	2	0	D	0	0	0	A	0	2	0	D
8	0	2	1	B	6	2	0	D	7	2	0	D	3	0	0	A					1	0	0	G	1	2	8	D
9	0	1	0	B																								
10	2	1	2	B	1	2	2	F	1	2	3	D	2	2	3	B	2	2	2	E					0	3	2	G
11	1	1	1	B	0	0	0	E	0	1	0	E	2	1	0	B	0	2	1	A					0	2	0	G
12	0	3	1	B	1	1	0	E	1	2	0	E	4	0	0	B	1	3	0	A	1	0	0	A				
13	0	0	1	C	0	0	0	D	1	0	0	D	0	0	0	A												
14	0	0	0	C	0	0	0	D	1	0	0	D	0	0	0	A	2	0	1	D	1	0	0	A	0	0	2	D
15	0	0	1	C																								
16	1	8	10	C	2	2	0	D	3	2	0	D	8	1	0	A	4	2	2	D	2	0	0	G	1	2	4	G
17	0	0	2	C																								
18	0	0	1	C	3	1	1	D	4	1	1	D	0	0	1	A	5	1	1	D	1	0	1	G	1	1	5	D
19					0	0	0	D	1	0	0	D	0	0	0	A	2	0	1	D	1	0	0	A				
20					0	0	0	E	0	0	1	E	0	0	0	B	0	1	0	E	0	0	0	F	0	2	0	D
21					0	0	0	E	0	0	1	E	0	0	0	B	0	1	0	A	1	0	0	A				
22									0	0	0	E	0	0	0	F	0	1	0	E	0	0	1	G	1	2	0	G

Table B.11: Comparison between the model (top) and HGO manual (bottom) solutions in terms of Continuity of Care between nurses and patients

	TT (min)	CC (score)	GAP (%)	Best Bound	Comp. Time (s)	Solution
1_F_14						
Min TT	223.03	7	0	223.01	76.55	Dom. by B
Max CC	271.93	22	0	22	141.27	Dom. by A
Nadir TT	251.78	22	0	251.76	205.54	A
Nadir CC	223.03	15	0	223.01	101.44	B
Min TT st CC=16	227.05	17	0	227.03	113.50	C
Min TT st CC=18	227.50	21	0	227.48	98.13	D
2P_F_14						
Min TT	223.03	6	0	223.01	98.29	A
Max CC	242.78	13	0	13	161.96	Dom. by B
Nadir TT	227.50	13	0	227.48	48.17	B
Nadir CC	223.03	6	0	223.01	55.34	A
Min TT st CC=7	226.32	9	0	226.30	87.63	C
Min TT st CC=10	227.05	12	0	227.03	103.90	D
1_G_16						
Min TT	177.97	13	0	177.95	128.91	Dom. by A
Max CC	260.83	30	16.67	35	3600.00	Dom. by F
Nadir TT		No solution			3600.00	
Nadir CC	177.97	18	0	18	1520.15	A
Min TT st CC=19	187.23	20	0	187.22	1263.66	Dom. by B
Min TT st CC=21	187.23	24	0	187.22	1500.80	B
Min TT st CC=25	191.82	26	0	191.80	674.21	C
Min TT st CC=27	211.75	27	3.50	204.35	3600.00	D
Min TT st CC=28	214.80	28	4.62	204.87	3600.00	E
Min TT st CC=29	258.80	30	21.20	203.94	3600.00	F
2N_G_16						
Min TT	177.97	13	0	177.95	134.95	Dom. by B
Max CC	266.70	30	13.33	34	3600.00	Dom. by A
Nadir TT	258.80	30	8.20	237.59	3600.00	A
Nadir CC	177.97	18	0	18	965.83	B
Min TT st CC=19	187.23	20	0	187.22	1731.11	Dom. by C
Min TT st CC=21	187.23	24	0	187.22	1956.32	C
Min TT st CC=25	200.22	25	0	200.20	2179.40	D
Min TT st CC=26		No solution			3600.00	
Min TT st CC=27	258.80	30	23.16	198.85	3600.00	A
1_A_18						
Min TT	180.78	36	0	180.77	346.54	Dom. by A
Max CC		No solution			3600.00	
Nadir TT			-			
Nadir CC	180.78	48	0	48	322.26	A
Min TT st CC=49	181.83	56	0	181.82	901.99	B
Min TT st CC=57	183.27	57	0	183.25	163.93	C
Min TT st CC=58	192.12	60	3.13	186.11	3600.00	D
Min TT st CC=60	192.12	60	0	192.10	1780.16	D
Min TT st CC=61		No solution			3600.00	
2S_A_18						
Min TT	162.97	34	0	162.95	267.543	Dom. by B
Max CC	237.18	64	3.13	66	3600	Dom. by A
Nadir TT	189.53	64	0	189.52	155.232	A
Nadir CC	162.97	36	0	162.95	254.292	B
Min TT st CC=37	163.00	37	0	162.99	64.195	C
Min TT st CC=38	163.05	39	0	163.04	181.781	Dom. by D
Min TT st CC=40	163.05	41	0	163.03	626.439	D
Min TT st CC=42	164.80	42	0	164.78	959.429	E
Min TT st CC=43	164.93	45	0	164.92	1447.949	F
Min TT st CC=46	165.10	46	0	165.08	400.413	G
Min TT st CC=47	166.20	47	0	166.19	707.455	H
Min TT st CC=48	170.37	48	2.85	165.51	3600	I
Min TT st CC=49	170.92	49	3.10	165.63	3600	J
Min TT st CC=50	171.87	51	0	171.85	2754.411	K
Min TT st CC=52	172.40	54	0	172.38	3149.265	L
Min TT st CC=55	174.92	55	0	174.90	1701.203	M
Min TT st CC=56	176.68	56	0	176.67	1584.242	N
Min TT st CC=57	177.27	57	0	177.25	1444.386	O
Min TT st CC=58	180.80	58	0	180.78	939.534	P
Min TT st CC=59	181.72	59	0	181.70	1097.683	Q
Min TT st CC=60	181.80	61	0	181.78	1110.324	R
Min TT st CC=62	184.48	62	0	184.47	282.797	S
Min TT st CC=63	189.53	64	0	189.52	276.394	A
3N_A_18						
Min TT	186.77	55	0	186.70	238.15	A
Max CC	224.62	60	3.33	62.00	3600.00	Dom. by B
Nadir TT	195.57	60	0	195.55	92.61	B
Nadir CC	186.77	55	0	186.72	449.51	A
Min TT st CC=56	188.48	56	0	188.47	266.52	C
Min TT st CC=57	195.57	60	0	195.55	1101.38	D
1_B_18						
Min TT	219.33	50	2.06	214.81	3600.00	Dom. by B
Max CC	240.62	68	0	68	25.26	Dom. by A
Nadir TT	221.27	68	0	221.27	42.89	A
Nadir CC	219.33	64	0	219.31	1679.38	B
Min TT st CC=65	219.57	65	0	219.55	52.69	C
Min TT st CC=66	221.27	68	0	221.27	28.27	A
2F_B_18						
Min TT	214.05	53	7.86	197.23	3600.00	Dom. by B
Max CC	244.73	68	0	68	593.42	Dom. by A
Nadir TT	219.67	68	0	219.65	45.26	A
Nadir CC		No solution			3600.00	
Min TT st CC=54	213.47	54	2.23	208.70	360.70	B
Min TT st CC=55	215.45	63	4.54	205.67	3600.00	C
Min TT st CC=64	215.85	64	0	215.83	238.16	D
Min TT st CC=65	216.48	65	0	216.46	487.51	E
Min TT st CC=66	219.67	68	0	219.65	257.69	A
3T_B_18						
Min TT	216.62	56	3.76	208.47	3600.00	B
Max CC	230.42	68	0	68	81.12	Dom. by A
Nadir TT	221.27	68	0	221.27	11.53	A
Nadir CC	216.62	56	0	56	1854.57	B
Min TT st CC=57	217.82	59	0	217.80	264.09	C
Min TT st CC=60	219.33	64	0	219.31	87.70	D
Min TT st CC=65	219.57	65	0	219.55	37.84	E
Min TT st CC=66	221.27	68	0	221.25	34.51	A
1_C_18						
Min TT	250	30	0	249.98	99.83	Dom. by A
Max CC		No solution			3600	
Nadir TT			-			
Nadir CC	250	32	0	32	388.69	A
Min TT st CC=33	251.17	33	0	251.14	472.38	Dom. by B
Min TT st CC=34	251.17	35	0	251.14	138.23	B
Min TT st CC=36	256.42	38	0.14	256.05	3600.00	C
Min TT st CC=39	256.83	45	1.19	253.79	3600.00	D
Min TT st CC=46		No solution			3600.00	
2P_C_18						
Min TT	250	34	0	249.75	359.14	Dom. by A
Max CC		No solution			3600.00	
Nadir TT			-			
Nadir CC	250	40	0	40	888.92	A
Min TT st CC=41	251.17	42	0	251.14	1620.49	Dom. by B
Min TT st CC=43	251.17	43	0	251.14	1288.70	B
Min TT st CC=44		No solution			3600.00	
1_D_22						
Min TT	332.967	58	12.0163	292.956	3600	Dom. by B
Max CC	425.817	65	35.3846	88	3600	Dom. by A
Nadir TT	335.8	70	13.607	290.108	3600	A
Nadir CC		No solution			3600	
Min TT st CC=59	318.5	64	9.15997	289.371	3600	B
Min TT st CC=71		No solution			3600	
2FT_D_22						
Min TT	301.70	53	12.24	264.77	3600.00	Dom. by B
Max CC	387.05	76	18.42	90	3600.00	Dom. by A
Nadir TT	311.32	76	14.48	311.32	3600.00	A
Nadir CC		No solution			3600.00	
Min TT st CC=54	295.48	59	12.44	258.72	3600.00	B
Min TT st CC=60	304.23	62	14.43	260.33	3600.00	C
Min TT st CC=63	306.55	64	16.34	256.47	3600.00	Dom. by D
Min TT st CC=65	305.70	66	15.42	258.57	3600.00	Dom. by D
Min TT st CC=67	311.12	67	16.60	311.12	3600.00	Dom. by D
Min TT st CC=68	310.77	68	15.86	261.48	3600.00	Dom. by D
Min TT st CC=69	305.03	70	14.98	259.34	3600.00	D
Min TT st CC=71	313.77	71	16.14	263.11	3600.00	Dom. by E
Min TT st CC=72	308.73	74	14.75	263.19	3600.00	E
Min TT st CC=75	312.48	75	14.76	312.48	3600.00	Dom. by A
Min TT st CC=77	317.27	77	15.56	267.91	3600.00	Dom. by G
Min TT st CC=78	314.67	78	13.25	272.99	3600.00	F
Min TT st CC=79	315.78	79	13.39	273.49	3600.00	G
Min TT st CC=80	318.37	80	13.69	274.78	3600.00	H
Min TT st CC=81	319.90	81	12.29	280.57	3600.00	I
Min TT st CC=82	324.13	82	12.71	282.94	3600.00	J
1_E_24						
Min TT	306.55	63	18.0417	251.243	3600.00	Dom. by B
Max CC	401.45	98	12.2449	110	3600.00	Dom. by A
Nadir TT	322.533	98	7.57121	298.114	3600.00	A
Nadir CC		No solution			3600.00	
Min TT st CC=64	299.50	72	14.77	255.26	3600.00	B
Min TT st CC=73	311.82	75	17.64	256.80	3600.00	Dom. by C
Min TT st CC=76	312.45	78	18.22	255.53	3600.00	Dom. by C
Min TT st CC=79	300.00	80	12.37	262.88	3600.00	C
Min TT st CC=81	327.75	86	22.12	255.25	3600.00	Dom. by D
Min TT st CC=87	316.93	87	15.42	268.06	3600.00	Dom. by D
Min TT st CC=88	307.57	88	11.62	271.83	3600.00	D
Min TT st CC=89	307.93	90	11.02	274.00	3600.00	E
Min TT st CC=91	312.22	91	14.45	267.10	3600.00	F
Min TT st CC=92	316.52	93	13.91	272.49	3600.00	Dom. by G
Min TT st CC=94	313.72	94	9.73	283.19	3600.00	G
Min TT st CC=95	319.02	96	11.27	283.08	3600.00	Dom. by H
Min TT st CC=97	317.55	97	7.95	292.31	3600.00	H
Min TT st CC=99	333.03	100	12.00	293.06	3600.00	I
Min TT st CC=101		No solution			3600.00	

Table B.12: Detailed results of the ϵ-constraint method applied to the literature instances