Routing and appointment planning optimization for medication at home: A case study in Isala hospital

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Abstract

Medication at home is novel and expanding service that hospitals offer to bring care closer to the patient. Nurses visit patients to administer parenteral medication at the patient's home. Patients have a specific requirement of medication requiring a suitable nurse for visiting and the required frequency of admission should be respected. Furthermore, working hour restrictions are considered. Routing and scheduling optimization enables optimal usage of resources, avoiding high logistical cost.

In this thesis, an novel ILP model is introduced to optimize the routes and schedules of nurses visiting the patients in medication at home services, where the total travel time over a schedule horizon is minimized. Two novel solution methods are proposed: a greedy algorithm, and large neighbourhood search algorithm. Real-life experiment data is derived from a large regional hospital in the Netherlands, including real-world travel times and medication data. Instances up to 90 visits over a one-week planning horizon are considered.

A comparison between measured travel time for the oncology department over 2019 and experiment results show that a decrease of 30% in average travel time per visit is possible with the optimization model. Experiment instances are created to examine the effects of visiting a larger number of patients over a fixed period, increasing the maximum allowed travel time from hospital to patients, additional skills and the introduction of multidisciplinary nurses, higher care frequency of patients and increasing the planning horizon. The results show that increasing the number of patients that are visited significantly lowers the average travel time per visit, while allowing patients to be visited that have more travel time from the hospital proves to have a negative effect by increasing the average travel time per visit significantly. Furthermore, the results show that increasing care frequency, additional skills and an increasing planning horizon have moderate negative effects on the average travel time per visit.

Computational results show that the developed large neighbourhood search method is able to devise results that are up to 31% worse compared to CPLEX solver in reasonable time, thereby showing that this method is a more time-efficient solving method. The greedy heuristic proves to be time-efficient but results are up to 83% worse compared to the large neighbourhood search method.

Contents

1. Introduction

The population of the Netherlands is growing to 19.3 million people in 2050 (NIDI & CBS, 2020). The share of people that are aged 65 or older in the Netherlands will grow from 3.4 million people now to 4.8 million in 2050 (NIDI & CBS, 2020). This growing elderly population increases the demand for healthcare and challenges the Dutch healthcare system to innovate for controlling cost, quality, and efficiency. One area of innovation is the transformation of hospital-based care to organizing care closer to the patient, in the community or at home (Deloitte, 2021). Home delivered care can range from monitoring a patient at a distance through digital technology, such as monitoring blood conditions, to the admission of medication at patient's home. Admission of medication has been the subject of innovation in Dutch hospitals.

In this research we focus on the planning and routing decisions involved in administering parenteral medication at the home of patients. The medication at home process treated in this research can be simplified to a nurse travelling from a hospital to a series of patients to administer parenteral medication to the patient. Parenteral medication consists of medication that is not administered orally to the patient. Examples of parenteral medication include subcutaneous oncology drugs and antibiotics that are administered intravenously.

Several decisions are to be made in the process of administering medication to patients at home; the amount of patients to treat, the amount of nurses required to treat the patients, the treatment order of patients, the assignment of nurses to patient and the time at which a patient is treated by a certain nurse (Isala Hospital, 2021). These decisions have many similarities with the decisions in "regular" home healthcare contexts, for example in delivering residential home care services, such as washing or bathing, to a patient. Furthermore, similarities with other problem types, such as a parcel delivery van delivering parcels to customers can easily be observed. Therefore, we classify the medication at home process as a home healthcare routing and scheduling problem (HHCRSP). According to Cissé et al. (2017), the "HHCRSP consists of designing a set of routes used by care workers to provide care to patients who live in the same geographical are and who must be treated at home".

Hulshof, Kortbeek, Boucherie, Hans, and Bakker (2017) distinguish planning decisions in healthcare by strategic, tactical, online operational and offline operational level. In home healthcare the following decisions have to be made (Hulshof et al., 2017):

- Strategical planning
  - Placement policy
  - Service mix
  - Case mix
  - Panel size
  - Districting
  - Capacity dimensioning
- Tactical planning
  - Capacity allocation
  - Admission control
  - Staff-shift scheduling
- Offline operational planning
  - Assessment and intake
  - Staff-to-shift assignment
  - Visit Scheduling
- Online operational planning
  - Visit rescheduling
  - Residential care services

This research covers both the tactical and the offline operational planning phase, since we focus on optimizing the routing and scheduling of appointments in medication at home services in relation to capacity allocation decisions. Although home medication is not specifically mentioned in the framework by Hulshof et al. (2017), we classify home medication in the healthcare planning and control context as a specific service in home care.

Isala hospital in Zwolle is a Dutch top-clinical hospital that recently piloted medication at home practices. Isala hospital provides parenteral medication for patients at home through various channels, and considers expanding the range of medication at home offered at patients' homes. However, challenges arise in the expanding of medication. For example, cost containment and efficiency are areas of concern. To answer these (business) questions of Isala hospital in medication at home, we execute a case study on the medication at home process of Isala and we analyse the effect of increasing patient demand for medication at home, the effect of increasing the maximum allowed travel time from hospital to patient and the effect of the number of different skills required in medication at home as well as several other effects.

The contribution of our research is as follows: First, we propose a novel ILP model that optimizes routing and appointment planning for medication at home. To the best of our knowledge, no research has been done on routing and appointment planning in the context of medication at home. Second, we show the impact in practice of our proposed approach through a case study in Isala hospital. In this case study we provide insight in the effects of maximum allowed travel time from hospital to patient, the effect of the number of different skills present in the process and the effects of an increasing amount of patients on the total travel time needed for visiting the patients.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature on HHCRSP. Section 3 provides an extensive description and mathematical problem formulation of the problem at hand. Section 4 introduces the methods for solving and generating a solution, whereafter Section 5 introduces the case study of the medication at home process in Isala hospital. In the case study, historical data from Isala hospital is used for experimenting and answering strategical and tactical (business) related to resource usage. The case study results are provided in Section 6, and we end with conclusions and discussion in Section 7.

2. Literature Review

Home healthcare is a promising and growing sector and most home healthcare providers historically did not use operations research (OR) tools in their operations before, which offers opportunities for improved design and optimization (Cissé et al., 2017). In the last decade however, home healthcare scheduling attracted increasing attention, as depicted by the available literature reviews on home healthcare scheduling (Cissé et al., 2017; Fikar & Hirsch, 2017).

While Fikar and Hirsch (2017) focus on the objectives and constraints of models in home healthcare scheduling, Cissé et al. (2017) develop an overview of OR models applied to HHCRSP. Various topics in HHCRSP are closely related to other research fields (Fikar & Hirsch, 2017), for example the field of home delivery operations and other vehicle routing problems.

To develop an overview of the body of knowledge on home healthcare routing and scheduling, this section discusses recent literature on HCCRSP. The literature has been filtered and selected based on predetermined criteria. Since the attention to home healthcare scheduling and HHCRSP is growing and to only provide an overview of recent literature, only articles published in the past 10 years were considered in the analysis. Furthermore, since our research has a strong operations research focus, only literature has been included that features an optimization model. Additional inclusion criteria can be found in Appendix 1. In total, 32 articles were selected for further analysis. The selected articles have been analysed on several characteristics, which we will discuss in the following sections. With these characteristics, we created a taxonomy, featuring model type (Section 2.1), objective functions used in the models (Section 2.2), planning horizons (Section 2.3), constraints (Section 2.4), solving methods (Section 2.5) and stochasticity (Section 2.6).

2.1. Model types

Many authors acknowledge that HHCRSP models are a development or extension of VRPTW (vehicle routing problem with time windows) problems (Ait Haddadene, Labadie, & Prodhon, 2019; An, Kim, Jeong, & Kim, 2012), with specific (home) healthcare objectives and constraints. Therefore, many similarities exist between fields of application of VRPTW models, such as used in service delivery or package delivery routing, and the home healthcare situation. Relevant variants of VRPTW introduced by authors include Multi-depot VRPTW (MDVRPTW) (Bard, Shao, & Wang, 2013; Liu, Yuan, & Jiang, 2019) and VRPTW with synchronization and preference (VRPTW-SP) (Ait Haddadene et al., 2019).

Most HHCRSP literature focuses on assigning a nurse/worker/vehicle/caregiver[1] to a patient/client[2], and on determining an optimal route for the nurse with corresponding patient appointments. However, some extensions are available in the literature. Some authors introduce a simultaneous VRP and facility location problem (e.g., Shiri, Ahmadizar, Mahmoudzadeh, and Bashiri (2020)). Simultaneous VRP and facility location problems are relevant in problems where the starting and ending location of the routes are not yet determined, which is typically not applicable to the hospital based medication at home processes. Zhan and Wan (2018) assign patients to a specific team and determine optimal routes for each nurse in a specific team, and classify this problem as a routing and appointment scheduling with team assignment (RASTA) problem, The RASTA problem differs in the team assignment component from "classical" HHCRSP models. Nikzad, Bashiri, and Abbasi (2021) introduce a SDDARP (stochastic districting, staff dimensioning assignment routing problem) model, which incorporates assigning patients and nurses to a geographical area and creating routes within these geographical areas.

While most models are of static nature, only the model proposed by Demirbilek, Branke, and Strauss (2019) is of dynamic nature. A dynamic model can process new information in each stage of the process and thus can make decisions online; at the moment of receiving new information on, for example longer travel time due to traffic or cancelling of appointments, routing decisions can be re-evaluated and re-optimized. On the contrary, static models only work with information known beforehand and therefore make decisions offline.

2.2. Objective functions

Traditionally, VRPs have objective functions that focus on distance or cost. The studied literature reveals that, while cost and distance are still frequently occurring, other objective functions are considered, such as waiting time (Baumann, 2018), tardiness (Dengiz, Atalay, & Altiparmak, 2019) or combinations of multiple indicators (Ait Haddadene et al., 2019; Baumann, 2018; Braekers, Hartl, Parragh, & Tricoire, 2016; Cinar, Salman, & Bozkaya, 2021; Doulabi, Pesant, & Rousseau, 2020; Hiermann, Prandtstetter, Rendl, Puchinger, & Raidl, 2015; Laesanklang & Landa-Silva, 2017; Nasir & Kuo, 2020; Taieb, Loukil, & Mhamedi, 2019; Wang, He, Li, & Wang, 2020; Zhang et al., 2019).

2.3. Planning horizon

The considered literature features various planning horizons ranging from daily to multiple weeks. Most models consider a daily scheduling and routing problem (Ait Haddadene et al., 2019; Baumann & Ieee, 2017; Bazirha, Kadrani, & Benmansour, 2020; Belhor, El-Amraoui, Delmotte, & Jemai, 2020; Braekers et al., 2016; Doulabi et al., 2020; Euchi, Zidi, & Laouamer, 2020; Hiermann et al., 2015; Laesanklang & Landa-Silva, 2017; Liu et al., 2019; Nasir & Kuo, 2020; Quintanilla, Ballestin, & Perez, 2020; Riazi, Chehrazi, Wigström, Bengtsson, & Lennartson, 2014; Shiri et al., 2020; Taieb et al., 2019; Wang et al., 2020). Patients in home healthcare often have recurring care demands (e.g., daily washing and clothing). Furthermore, patients have varying period lengths of receiving care. Using a longer planning horizon may therefore better represent the real-world situation, in which information on the care that is to be given the next two weeks is already available. An et al. (2012) treat patients with different care intervals differently, by assuming that patients with a high care frequency (e.g., every one to three days) have more influence on the schedule than patients with a low care frequency. Castaño and Velasco (2020) use a multiple-model setup to assign patients to nurses, create optimal routing for the patient-nurse combination and optimizing the workload of nurses over multiple days. The model of Castaño and Velasco (2020) can also be used to determine the number of workers required to cover expected future patient requests. Hewitt, Nowak, and Nataraj (2016) use a consistent-VRP, a VRP with a fixed nurse-patient combination, over a longer planning horizon. Shao, J. F. Bard, and A. I. Jarrah (2012) decompose a planning horizon of multiple days into subproblems per day and optimize the local subproblems using local neighbourhood search. While longer planning horizons may offer efficiency gains (Hewitt et al., 2016), complete information for the whole planning horizon may not be available at the moment of planning (and optimizing) and thus uncertainty and/or dynamic updating has to be introduced in the data and/or modelling approach.

[1] We mention multiple terms for the object that travels from hospital to patient (and consequently patient to patient), since literature labels them variously. In the remainder of this report, the term "nurse" will be used, while in fact, we mean a nurse with a relevant mode of transport.
[2] We mention multiple terms for the object that is visited by the nurse, since literature labels them variously. In the remainder of this report, the term "patient" will be used, while in fact, we mean a location at which a service is delivered or a delivery is made.

2.4. Constraints

The models introduced in the literature feature the following constraints, which we group by *basic constraints* and *additional constraints*. We classify the following constraints as basic constraints, which are featured by all authors in the considered literature:

- Demand: all demand for care should be fulfilled within the available time;
- Capacity: capacity (either in load or time) cannot be violated.

Additional constraints that are included by a subset of authors include:

- Preference: patients have a preference for specific nurse(s) or are assigned to a specific nurse to assure continuity of care;
- Nurse Qualification: Nurses have different skill levels or can only execute certain operations for a patient;
- Time Windows: Patient have one or more time windows in which they are available to receive care;
- Synchronization: Two nurses are required to be at one patient at the same time, or delivery of medication or other objects and the appointment with the nurse should be scheduled sequentially;
- Working Regulations: Lunch break and/or other working regulations are considered.

The additional constraints vary in complexity, and are modelled according to that complexity. Table 1 provides an overview of the complexity of the constraints featured in the models.

Constraint type	**Simple**	**Average**	**Complex**
Preference	No preference	Patient has fixed nurse unless not available	Patient has one fixed nurse; no other nurse can be selected
Nurse Qualifications	No nurse qualifications involved		Nurse should have the right skill for the involved medication
Time Windows	No time windows	Soft time windows, can be violated by incurring penalty	Hard time windows, cannot be violated
Synchronization	No synchronization		Two or more nurses should be at the same location at the same time
Working Regulations	Only working hours of nurses	Working hours and break times	Overtime

Table 1: Constraint complexity overview

Figure 1 shows an overview of the model features. Most models have time window constraints, which, as mentioned in Section 2.1.1, can be attributed to the fact that most models are an extension of VRPTW models. Preference, nurse qualifications, and working regulations are other popular constraints for the models in the considered literature. Nurse qualifications and patient preference (and thereby continuity of care) are obviously important practical concerns in delivering healthcare to patients. An implementation example of nurse qualification is given by Castaño and Velasco (2020) who model different services with various skill-requirements, with more expensive services provided by highly qualified nurses. Another example is the implementation given by Ait Haddadene et al. (2019), who introduce a set of services for patients and each nurse is able to provide a subset of these services. Preference features are modelled in various ways; Heching, Hooker, and Kimura (2019) model preference constraints by assigning a fixed nurse to a client, while Shao et al. (2012) modelled preference by using hard constraints regarding patient-nurse combinations and nurse working environment preferences.

All literature considers a maximum working time for nurses. Furthermore, some authors include working regulation extensions, such as lunch breaks. As an example, Bard et al. (2013) implement working regulations by requiring a 30 minutes break between 11:00 am and 1:00 pm for each nurse. Baumann (2018) subtracts the break time from the total waiting time of employees and Di Mascolo, Espinouse, Gruau, and Radureau (2017) require each nurse to have a break of 20 minutes on each six hours of working. The nature of the working regulations constraints is, in most cases, formed by the local legislation on working hours (Di Mascolo et al., 2017). Bazirha et al. (2020) introduce overtime for nurses by incurring a penalty whenever a nurse works in overtime.

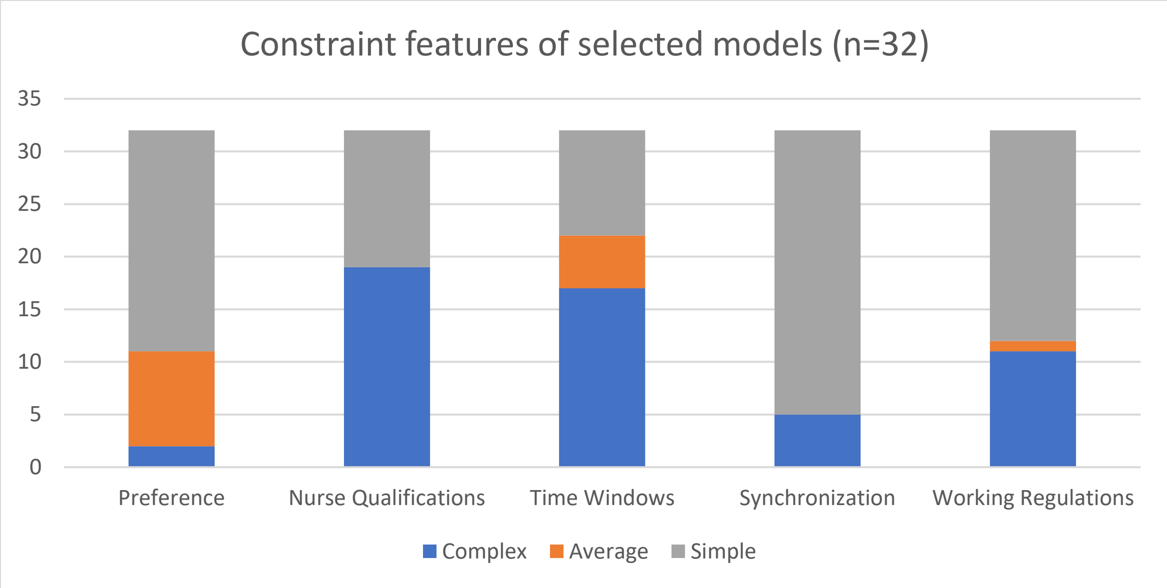

Figure 1:Overview of model constraint features in the analysed literature

2.5. Solving Methods

As mentioned in Section 2.1, most HHCRSP models in the considered literature are an extension of VRPTW models. VRPTW models are NP-hard problems (Hiermann et al., 2015) and solving these problems exactly with real-life instances is often too time-consuming. Therefore, authors frequently propose heuristic or approximation methods for solving the models.

A popular choice for solving VRPTW and HHCRSP models are metaheuristics: K. Braekers, Ramaekers, and Van Nieuwenhuyse (2016) show in their review of VRP (and extensions) models that metaheuristics are a popular solving method for VRPTW models: 71% of the considered literature features metaheuristics as solving methods. Genetic algorithms are used by Ait Haddadene et al. (2019), Bazirha et al. (2020) and Nasir and Kuo (2020). Braekers et al. (2016), Cinar et al. (2021); Hiermann et al. (2015); Shao et al. (2012) and Veenstra, Roodbergen, Coelho, and Zhu (2018) use (adaptive) variable neighbourhood search methods. Simulated annealing methods are proposed by Zhang et al. (2019) and Hiermann et al. (2015). Zhan and Wan (2018) use Tabu Search as solving method. Wang et al. (2020) use a (hybrid) whale optimization algorithm. Euchi et al. (2020) use ant colony system optimization. The aforementioned authors all show that metaheuristics can generate solutions close to optimal in reasonable time, even with larger or real-life problem instances.

While exact methods typically feature high computation times, Baumann (2018), Bard et al. (2013), Chen, Rubinstein, Smith, and Lau (2017), Dengiz et al. (2019), Hewitt et al. (2016), Moussavi, Mandjoub, and Grunder (2019) and Taieb et al. (2019) choose to solve their models exactly by using a computational solver (often CPLEX). Castaño and Velasco (2020) and Heching et al. (2019) opt for a Benders-approach by decomposing the main problem into multiple subproblems thereby improving the computation time needed for solving, similar to Laesanklang and Landa-Silva (2017) that use decomposition based on geographical clusters. Chen et al. (2017) use Lagrange relaxation for solving their mathematical model, and Doulabi et al. (2020) use an L-shaped algorithm for solving to optimality under stochastic travel times. Liu et al. (2019) use a branch and price algorithm to solve their proposed problem stochastic service and travel times. While exact methods generate optimal (or near-optimal results when integrality gaps are allowed or decomposition is applied), computation times are high for large instances (i.e., more than 100 patients) or even intractable due to the large amount of computer memory required. Bard et al. (2013) show that exactly solving their problem with around 500 visits including time windows and 20 therapists can take up to around 15.000 seconds (4 hours) of computation time, showing that for real-life, large problem instances solving to optimality is very time-consuming.

An et al. (2012) use a problem-specific heuristics for solving, consisting of a construction and insertion component for creating schedules. Cinar et al. (2021) propose a heuristic for assigning patients to a day and show that their heuristic is competitive with neighbourhood search strategies in terms of computation time. Nikzad et al. (2021) use a two-stage stochastic model and solve it by introducing a heuristic that determines an initial solution, fixes the solution in case of infeasibilities, and then improves the obtained solution when possible. Although a complex method, Nikzad et al. (2021) show that their method is faster than solving exactly while performance in terms of objective function is only slightly reduced. Riazi et al. (2014) propose a gossip algorithm, adapted from Franceschelli, Rosa, Seatzu, and Bullo (2012) that uses a decomposition approach and solves subproblems exactly using a computational solver (CPLEX), showing that the method is competitive with other common methods.

2.6. Stochasticity

Uncertainty in parameters is taken into account by only 25% of the analysed literature. Bazirha et al. (2020) introduce a recourse estimation procedure that comes into play when (soft) constraints are not respected. Bazirha et al. (2020) use penalty cost for tardiness of the operations and a compensation for the overtime of nurses. Chen et al. (2017) model travel times and visit duration as random variables and introduce chance constraints for time windows and time budget constraints. To use these chance constraints, Chen et al. (2017) use the Sample Average Approximation (SAA) technique to generate a large amount of uncertain parameter samples that are then used in the chance constraints. Demirbilek et al. (2019) use a scenario-based approach that suits the dynamic model they are using. A collection of scenarios is used as input for the model and hereby the model is evaluated for handling uncertainty. Doulabi et al. (2020) model uncertainty using a two-stage model where the second model is used to determine optimality under a generated set of instances with uncertain visit duration and travel times. Liu et al. (2019) propose a similar approach as Chen et al. (2017), but treat arrival and departure times as random variables themselves. Shiri et al. (2020) apply the Mulvey approach; optimizing for a set of scenario's using a two-phase approach. Zhan and Wan (2018) use a scenario-based approach for the unknown parameters, but require that no constraints are violated, thereby this is different implementation than chance constraints.

3. Problem description

Section 3.1 describes the routing problem of the medication at home process. Section 3.2 introduces the formal representation of the problem.

3.1. Problem formulation

The medication at home process is characterized by three important components: patients, nurses, and drug types. Each patient features a location, a drug type, and an admission frequency. The admission frequency for the patient is determined by the drug type and, in some cases, by the medical state of the patient. For example, a patient with low health may have a higher admission frequency for a specific drug then a patient who is in good condition.

Each drug has a specific skill that is required from the nurse. These skills are mainly based on the type of drugs. For example, oncological drugs require a nurse specialized in oncology and cardiology drugs require a nurse specialized in cardiology. Each drug has a drug dependent admission time, which is the actual time it takes to administer the drugs.

A nurse always starts a route at the hospital, where medication for all patients in the route is collected and checked before travelling to the first patient. When arriving at a patient, the nurse checks the health status of the patient and checks the identity of the patient. For some medication, a video/audio connection is established with a nurse at the hospital to confirm the identity of the patient and to check the drugs that are to be administered to ensure patient safety protocols are followed. The nurse starts administering the patient if no irregularities occur. During the admission, the health status of the patient is monitored by the nurse. After admission, the nurse registers the admission in the IT-systems of the hospital. After leaving the patient, the nurse travels to the next patient on the route (if any left) or travels back to the hospital and finishes the route.

The routing and appointment planning includes the following constraints:

- The sum of travelling time and working time on a day should be limited to the working hours of the nurse;
- A nurse should have the right skill level for medication that is to be administered;
- Patient appointments cannot overlap or be pre-empted. That is the starting time of appointment B should not be earlier than the starting time of appointment A, plus the entire processing time of appointment A, plus the travelling time from A to B.

We consider decentral appointment planning, where all patients and their medication are known at the time of scheduling. Since there typically is a preselection of the patients that are admitted to the medication at home program, all patients that are scheduled to have an appointment should be visited. We assume that a patient is only allowed in the medication at home programme if capacity exists to treat the patient. The preselection criteria depend on the hospital settings, and typically include a check on the health status of the patient, the home situation of the patient, the type of medication, and the location of the patient. For example, the cast study hospital Isala only allows patients that live within 30 kilometres of the hospital to participate in the medication at home program for the administration of parenteral medication, and the administering of the medication should not take more than 30 minutes.

The process described above represents a situation where a hospital nurse travels to a patient with the medication. Other types of medication at home processes are also possible. In our case study hospital, we furthermore identify the following variants of medication at home:

- A patient collecting medication in the hospital at the time of leaving from a previous consultation or admission, the administering is done by a nurse of a (local) home care organization;
- A commercial pharmaceutical company delivers the medication to the patient, the administering is done by a nurse of a (local) home care organization;
- A commercial pharmaceutical company delivers both the medication and the nurse to administer the drugs.

3.2. Problem formulation (model)

In this section we translate the problem definition from the previous section to a mathematical problem formulation. We opt to approach the model as a classical HHCRSP, where we assign a nurse to a patient and determine the optimal route for a nurse on a given day. While the concept of approach is not a new one, to the best of the author's knowledge, no similar models exist in the field of medication at home. We opt for using an objective function solely focussing on minimizing travel time. Since cost are mostly derived from time resource usage, assuming equal cost factors, having travel time as objective function leads to the same results as minimizing on cost. Furthermore, while travel times are optimizable by changing the sequence(s) of patients, treatment or visit times are not, as they are mostly fixed by medication restriction or patient characteristics. The planning horizon we use in our model is not fixed. However, we note that the operational nature of the schedule makes planning horizons of two weeks or more not relevant.

Qualifications of nurses are modelled by introducing a binary variable that enables (or disables) patient-nurse combinations. Working regulation are implemented by introducing constraints for working hours and lunch breaks. The reviewed literature shows these constraints are not new and are already used in a significant amount of literature.

Parameters in the model are of deterministic nature in the model. However, by introducing multiple scenarios the influence of uncertainty of parameters (for example travel time or visit duration) can be examined.

We consider a single period model that creates a routing and appointment planning for the nurses and patients in medication at home. The planning horizon (in days) is defined as $T = \{0, .., t\}$, with t being a day in the planning horizon. The set of patients is denoted by $P = \{0, \dots, p\}$ with p the total amount of patients the planning horizon and p = 0 representing the hospital. The set of nurses is denoted by $K = \{1, \dots, k\}$ with k the total number of nurses available over the planning horizon. The travel time (in minutes) from patient $i \in P$ to patient $j \in P$, $i \neq j$, is denoted by t_{ij}. The start and end time of the work shifts from nurse $k \in K$ on day $d \in T$ are respectively denoted by ws_k^d and we_k^d. The required visit duration (in minutes) for patient $i \in P$ receiving medication is defined by v_i. A binary and predetermined parameter c_{ik} describes whether patient $i \in P$ can be visited by nurse $k \in K$. If c_{ik} has the value 1, nurse k can visit patient i, when 0 nurse k cannot. c_{ik} can be used for modelling skill requirements of nurses as well as continuity of care. We define continuity of care as a condition that a patient is only visited by one specific nurse. The required care interval in days of patient i is denoted by e_i.

Two types of decision variables are used in the model. $X_{i,j,k}^d$ takes the value of 1 if a nurse k directly visits patient j after patient i on day $d \in T$, and 0 otherwise.

Furthermore, three auxiliary variables are used in the model. Y_i^d takes the value of 1 if patient i is assigned to day $d \in T$, 0 otherwise. S_{ik}^d is a non-negative variable indicating the starting time (in minutes) of the visit at patient i. W_k^d is a binary value that takes value 1 if nurse k is working on day t of the planning horizon, 0 otherwise.

Table 2 provides a summary of the model notation.

Sets	
$T = \{0, .., t)$	Planning horizon
$P = \{0, \dots, p\}$	Set of patients and hospital indexed zero
$K = \{1, \dots, k\}$	Set of nurses
Parameters	
$t_{i,j}$	Travel time from patient i to patient j, $i \neq j$
v_i	Required visit duration for patient i
ws_k^d	Work shift start time of nurse k on day d
we_k^d	Work shift end time of nurse k on day d
c_{ik}	Binary variable indicating if patient i is compatible (1) or not (0) with nurse k
e_i	Care interval of patient i
Auxiliary variables	
W_k^d	Binary variable indicating whether nurse k works on day d (1) or not (0)
Y_i^d	Binary variable indicating whether patient i is treated on day d

S_{ik}^d	Non-negative variable indicating the starting time (in minutes) of visit at patient i
Decision variables	
$X_{i,j,k}^d$	Binary variable indicating whether patient i is visited after patient j by nurse k on day d (1) or not (0)

Table 2: Summary of model notation

The objective function aims to minimize the total travel time of the nurses during the planning horizon:

$$\min \sum_i \sum_j \sum_k \sum_d X_{i,j,k}^d * t_{i,j}$$

The objective function is subject to several constraints. Constraint (1) ensures that each patient that is assigned to a day, is also assigned to a route.

$$\sum_j X_{i,j,k}^d = Y_i^d \ \forall \, i,d,k \quad i \neq j \tag{1}$$

Constraint (2) ensures patient appointments cannot overlap. Therefore, the starting time of the appointment, together with the visit and the travel time to the next patient for a patient is lower than or equal to the starting time of the next patient.

$$S_{ikd} + v_i + t_{ij} \leq S_{jkd} + M\left(1 - X_{i,j,k}^d\right) \ \ \forall \, i,j \in P, k \in K, d \in T \quad i \neq j \tag{2}$$

Constraint (3) represent the flow constraints. If a nurse arrives at a patient, the nurse should also leave that same patient.

$$\sum_i X_{i,j,k}^d = \sum_i X_{j,i,k}^d \, \forall \, j \in P, \ k \in K, d \in T, i \neq 0, j \neq 0 \tag{3}$$

Constraint (4) and (5) ensure that the routes of nurses on a day always start and end at the hospital (recall that the hospital has location index zero).

$$\sum_i X_{0,i,k}^d = 1 \ \forall \, k \in K, d \in T \tag{4}$$

$$\sum_i X_{i,0,k}^d = 1 \ \forall \, k \in K, d \in T \tag{5}$$

Constraint (6) determines that the starting of the first appointment for a nurse on a day is always later than the working start time of the nurse and the travel time of the hospital to the first appointment. Note that if a patient is not visited, this constraint is always valid by using the big-M.

$$ws_k^d + t_{0j} - M\left(1 - Y_{j,k}^d\right) \leq S_{jkd} \, \forall \, j \in P, k \in K \, , \ j \neq 0 \tag{6}$$

Alternatively: Use the fact that S is a non-negative variable $S_{ikd} + M\left(1 - X_{0jk}^d\right) \geq t_{0,j}$

Constraint (7) represents the requirement that the end time of a route is always earlier or equal to the end of the work shift time of a nurse. Note that if a patient is not visited, this constraint always valid through use of the big-M method.

$$S_{ikd} + v_i + t_{i0} \leq we_k^d + M\left(1 - Y_{i,k}^d\right) \forall \, i \in P, k \in K, i \neq 0 \tag{7}$$

Constraint (8) ensures that the care interval of the patient is restricted and that, for example, a patient with a care interval of two days is not visited two days in a row.

$$Y_i^d = Y_i^{d+e_i} \, \forall \, i, d \in \{0,..,T - e_i\} \tag{8}$$

Constraint (9) ensures that the patient is minimally visited the planning horizon divided by the visiting interval times in the planning horizon. We round down to prevent that, for example, a patient with an interval of two days will be visited four times in a period of seven days, which is not possible considering constraint (8). Since Y_i^d is a binary variable, a patient is always visited at least once in the planning horizon, which is a reasonable assumption.

$$\sum_d \sum_k Y_i^d = \left\lceil \frac{T}{e_i} \right\rceil \forall \, i \tag{9}$$

Note that by rounding down in the right hand side of this constraint, a misalignment can occur when solving two sequential schedules since a patient can have too few appointments looking at both schedules. To illustrate this, a quick example suffices. Say patient A needs medication every two days. When creating a schedule for one week (seven days), the patient would, by rounding down, need three visits. Creating a schedule for one week after the week after which we already created a schedule, the patient would again need three visits. The patient then has, on a total of 14 days, six appointments while needing seven, assuming the patient needs more than seven appointments in total.

Constraint (10) ensures that a patient is only assigned to one nurse per day, preventing that a patient is visited twice per day.

$$\sum_k Y_i^d \leq 1 \; \forall \, i, d \tag{10}$$

Constraint (11) makes sure that the variable W_k^d is set to 1 if a nurse is starting a route at the hospital and thereby indicates whether nurse k is working on day d.

$$W_k^d \geq \sum_j X_{0,j,k}^d \; \forall \, k, d \tag{11}$$

Constraint (12) makes sure that a patient is only visited by a nurse that is compatible with the patient.

$$\sum_j X_{i,j,k}^d \geq \; c_{ik} \, \forall \, i, d, k \quad i \neq j$$

Constraints (13) – (15) ensure binary value for the variables. Constraint (16) is a non-negativity constraint for the starting time variable.

$$X_{i,j,k}^d \; \in [0,1] \; \forall \, d, i, j, k \tag{13}$$

$$Y_{i,k}^d \quad \in [0,1] \; \forall \, d, i, k \tag{14}$$

$$W_k^d \quad \in [0,1] \; \forall \, d. k \tag{15}$$

$$S_{ikd} \; \geq 0 \qquad \forall \, d, i, k \tag{16}$$

Note that we do not consider lunch breaks in the model directly, but implement these afterwards by starting the lunch break at the start time of an appointment during the lunch break period, for example between 11:00 am and 1:00 pm. Starting times of the appointments *after* the lunch break are delayed by the lunch break time. To compensate for the added time, the working time is reduced with the required lunch break time.

Furthermore, weekends are not explicitly considered in the problem formulation. Real-world situations may require weekend days to be only used whenever required by medical reasons to avoid many appointments in the weekend that may have higher cost than during weekdays. Of course, considering weekends depends on the considered planning horizon. A penalty may be introduced for appointments that are scheduled on weekend days, thereby minimizing unnecessary costly appointments. This penalty may follow naturally from higher costs during weekends, but can also be introduced manually by introducing a daily cost factor a_d in the objective function of the model. The adapted objective function would then be:

$$\min \sum_i \sum_j \sum_k \sum_d X_{i,j,k}^d * t_{i,j} * \boldsymbol{a_d}$$

In the standard case, we assume that there are always enough nurses available to create a feasible schedule. An adaption to the model can be made to minimize the number of nurses needed to execute the schedule by changing the objective function of the model to:

$$\min \sum_i \sum_j \sum_k \sum_d X_{i,j,k}^d * t_{i,j} + \; \sum_d \sum_k W_k^d * \; f_k$$

Where f_k represents the fixed cost per nurse if a nurse is working on day t.

We assume that all input parameters are deterministic, e.g., no stochasticity is incorporated in any parameter of the model.

The formulated problem can be classified as an NP-hard problem, as already described in Section 2. We therefore, reside to heuristics for solving the problem for larger problem instances, as discussed in Section 4.

4. Solution methods

Considering the complexity of HHCRSP's and the fact that solving exactly is too time-consuming for large problem instances, the use of metaheuristics is an attractive alternative to limit computation time while still generating solutions that are near-optimal, as we have shown in Section 2.5. We opt for two solution methods: a greedy heuristic based on simple rules resembling planning in practice and a metaheuristic in the form of an adaptive large neighbourhood search (ALNS). It has been proven by Pisinger and Ropke (2007) that ALNS is a suitable and well-performing metaheuristic for VRP problems. As pointed out in Section 2, VRP problems share many characteristics with HHCRSP's. We therefore opt for implementing the ALNS for our specific HHCRSP problem. To the best of our knowledge, we are the first to implement ALNS for a HHCRSP problem. Section 4.1 will introduce the Greedy Heuristic, Section 4.2 will introduce the ALNS heuristic.

4.1. Greedy Heuristic

The main core principle driving the greedy heuristic is the pairwise scheduling of patients close to each other. Furthermore, nurses with a low number of skills and thus very specialized, are selected first for treating patients, while nurses with a higher number of skills are used with lower priority. The selection of patients is based on the highest care interval. The higher the care interval the more appointments are to be made on the schedule and therefore these will have more influence on the performance of the schedule than patients with low care intervals. Patients with highest care interval will therefore be selected first to be scheduled. Figure 2 shows the greedy heuristic in flowchart format.

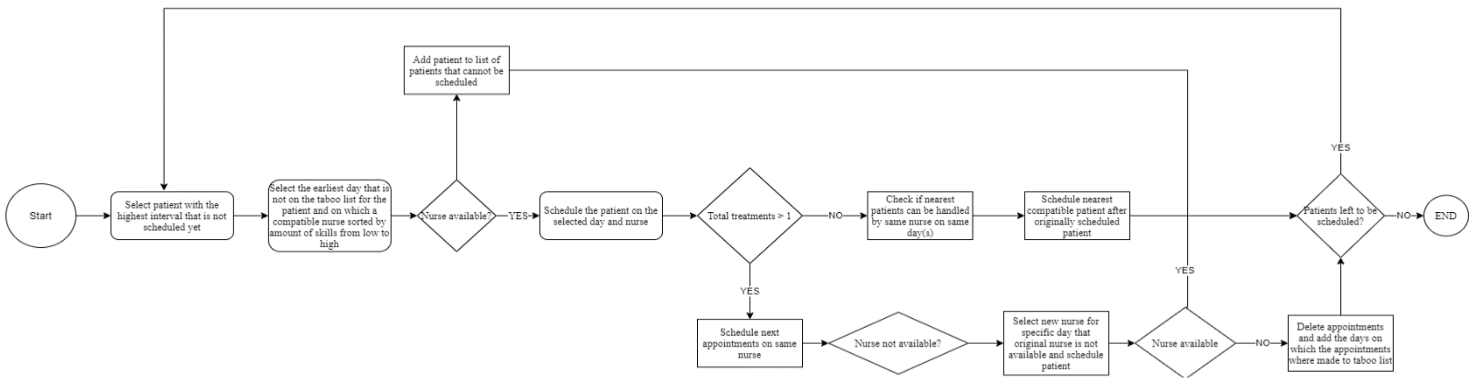

Figure 2: Greedy Heuristic in flowchart format

The output of the greedy heuristic can also be used as input for the ALNS heuristic. However, we opt for using the aforementioned constructive heuristic based on randomness.

4.2. Adaptive Large Neighbourhood Search

A simulated annealing (SA) algorithm forms the core of the ALNS framework. For the simulated annealing framework we follow the implementation proposed by Arora (2004).

In each iteration k of the simulated annealing algorithm, a selection of operators is used for exploring neighbourhood solutions of the current solution. The adaptivity of the framework is introduced by tracking the performance of the used operators and choosing operators according to their relative performance. The performance score of each destroy- and insertion operator is tracked by respectively π_i for the destroy operators and ρ_i for the insertion operators. π_i and ρ_i are updated by σ if the used operator leads to a better solution than the current one. We differ from the implementation by Pisinger and Ropke (2007) by using only one type of 'reward' for the operators and not tracking whether a solution has already been found. Due to the solution being a large collection of numbers, tracking and storing complete previous solutions is computational and memory-wise too demanding.

As can be derived from Section 3, relevant decisions for the appointments of patients are the day on which they are scheduled, the nurse that handles the appointment and the order of the appointments on a single day. A neighbourhood solution can therefore be created by changing the day of an appointment, changing the nurse for an appointment, changing the order of appointments or a combination of these changes, given not violating any constraints. We follow the implementation as proposed by Pisinger and Ropke (2007) and distinguish by a removal and inserting operators. Removal operators select one or multiple appointment(s), depending on the degree of destruction, which we remove from the schedule and temporarily store in a pool of unscheduled patients. An insertion operator is used to determine the place on the schedule where the one or more of the appointments in the pool of unscheduled appointments is placed.

We use the following removal operators:

- Random removal: randomly selecting one (or multiple) patients to remove from the schedule. Remove all scheduled visits from the schedule
- Remove biggest gap: select the patient(s) that has the most summed travel time from the preceding patient(s) and to the next. Remove all the visits from the selected patient from the schedule.

The standard degree of destruction (the number of patients we remove per iteration) used in this research is one.

The following insertion operators are used:

- Random inserting: randomly select a feasible day, (compatible) nurse, and position on the schedule. If multiple visits have to be scheduled, the care frequency is respected by deriving the next day of visit from the first day a visit is scheduled while still selecting a random (compatible) nurse and position.
- Best pairs: searching the nearest candidate on the schedule and scheduling the patient before or after the appointment of this nearest candidate to minimize travel time.

The complete ALNS algorithm:

Step 1: Initialize the starting temperature T_0, the iteration counter $k = 0$, the integer variable representing the maximum iterations (Markov chain length) L, parameter α and starting solution x_0.

Step 2: Generate a new neighbourhood solution x by generating random number α.
If $\alpha \leq \frac{\pi_1}{\pi_1 + \pi_2}$, select destroy operator 1. Else select destroy operator 2.
Generate random number β.
If $\beta \leq \frac{\rho_1}{\rho_1 + \rho_2}$, select insertion operator 1. Else select destroy operator 2.

Compute the difference in performance $\Delta f = f(x) - f(x^0)$

Step 3: If $\Delta f < 0$ (the new solution performs better), we accept the new solution as the new solution $x^0 = x$, add σ to the scores of the selected destroy and insertion operators π_i and ρ_i, and proceed to Step 4. If the new solution also performs better than all solutions found to this point, we accept the solution as new best solution $x^{best} = x$.
If the new solution performs worse than the old solution ($\Delta f \geq 0$), we calculate the probability density function: $p(\Delta f) = exp^{(\frac{\Delta f}{T_k})}$ and we draw a random number z uniformly distributed in [0,1]. If $z < p(\Delta f)$ we accept the new solution as the new solution $x^0 = x$ and proceed to Step 4.

Step 4: We iterate $k = k + 1$ if $k < L$. If $k \geq L$ and the stopping criterion is satisfied ($T \leq 0.1$), we terminate the algorithm and return x^{best}. Otherwise go to Step 5.

Step 5: Set $K = K + 1$, $k = 1$ and set $T_k = (1 - \alpha) * T_{k-1}$, return to Step 2.

The ALNS metaheuristic can only be initialized using a feasible starting solution. Without a starting solution, no neighbourhoods can be explored, as these are non-existent. We create a feasible solution by scheduling patients on a random day with a random feasible nurse and adhering to the constraints introduced in Section 3. After randomly selecting a patient, a day and a feasible nurse, the heuristic checks whether possible follow-up appointments derived from the care frequency are needed and if they can be planned too on the same nurse, or whether a different nurse is needed. Since the constructive heuristic features no optimization components, we expect the metaheuristic to quickly explore neighbourhood solutions and improve performance.

Both the designed ALNS algorithm and the greedy heuristic are implemented using Python 3.8 and the ILP model is implemented in AIMMS with CPLEX solver 20.1 and run on a computer with an Intel Core i7-4710HQ CPU.

5. Case Study / Experimentation

5.1. Medication at home at Isala

Figure 3: The main building of Isala hospital Zwolle. Retrieved from: www.isala.nl

The case study is conducted at Isala hospital group. We will refer to Isala hospital group with 'Isala' in the remainder of this paper. Isala is a large regional hospital with around 7000 employees and 5 locations in the region of Zwolle, with Zwolle also being the main and largest location of the hospital group. Isala has already piloted medication at home processes and in some cases medication at home is regularly offered to patients. Currently, the care specialisations oncology and cardiology offer medication at home. Furthermore, antibiotics and a range of other intravenous medication is offered through external parties or administered by local (home) care organisations.

Transferring care from the hospital to patient's home offers benefits to the patient according to Isala. A benefit for patients is that patients receive care in their own safe environment and travelling to the hospital, which can be very demanding for sick patients, is reduced. Furthermore, the stress patients experience during the treatments is significantly lowered when patients receive medication at home versus receiving the medication at the hospital (Isala Oncology Department, 2020). Since Isala is rating these benefits as high, Isala has planned to scale up medication at home practices by expanding the group of patients that receive care at home and the types of medication that are offered at home.

Planning of the appointments for medication at home is currently done in a semi-manual and decentral manner. That is, the appointments for a day are planned manually by each department involved in medication at home. However, in some departments, the routes are planned with a tool freely available on the internet that optimizes routes based on input addresses.

Many actors are involved in medication at home, which causes information and responsibility to be dispersed throughout the processes. One goal of the Isala is to place control of the medication at home processes at a central point to improve efficiency of- and control on the processes. A consequence of this goal is that the hospital is interested in a situation where external organizations are cut out of the process. One objective of the case study is therefore to assess the effects of increasing the patients that receive medication at home on the resources needed to execute the treatments. Since our research is only focused on Isala, the modalities of planning and routing by local (home) care organisations and commercial pharmaceutical company are not considered.

The selection of patients that are eligible for medication at home from the oncology & cardiology department is based on several factors, including the distance from the hospital to the patient. Both departments use a maximum driving distance of 30 kilometres, above that a patient is not eligible for receiving medication at home. While increasing the distance may lead to higher travel times, the hospital is interested in the effects of increasing or decreasing the maximum distance for patients that receive medication at home.

To guarantee safe administering of the medication, nurses should have the right skills for administering certain types of medication. Currently, nurses of the different departments administer the medication at patient's homes, oncology medication is therefore always administered by specialised oncology nurses. External parties, for example home care organisations, often have specialised teams for certain types of medication. Isala is interested in the effects of combining specialisations such that nurses can treat a wider range of patients in home medication and thus nurses being multi-disciplinary. Note that the medical aspects of implementing multi-disciplinary nurses in medication at home is not part of this research and may pose restrictions to the possibilities of implementation.

To summarize, Isala has interest in the following insights:

- The effect of increasing the number of patients that receive medication at home on resource use.
- The effect of maximum travel distance or time from hospital to patient on the resource use.
- The resources needed to handle medication that is currently administered by other care organisations.
- The performance benefits that might apply by introducing nurses that have multiple skills and can handle treatment and medication from multiple disciplines.

To develop insights in the aforementioned topics, we will assess these topics in Section 5.3 by developing experiment scenarios that will serve as input for the models that we have developed in Section 3 and 4. Before that, we will assess the available data in Section 5.2.

5.2. Available Data

In this section, we assess the data of the medication at home operations that is currently available.

5.2.1. Medication types and characteristics

There is a wide range of medication administered at patients' homes. Each treatment with medication features a different nursing skill required, which is mostly related to care specialties. For example, oncology medication is administered by oncology nurses. Furthermore, visit durations differ per medication. Isala has chosen to only administer medication with an administering time of 30 minutes or less to minimize the time that a nurse must be present at a patient's home. However, these 30 minutes do not include the preparation of the medication and the identification of both the patient and the medication. Therefore, the available data shows that the duration of a nurse visiting a patient is often longer than 30 minutes. The identification of the patient and medication is done by the four-eyes principle. A nurse at the patient location has a video or voice connection with a nurse who is at the hospital to confirm that the nurse is going to administer the right type of medication to the right patient. These steps are very important regarding patient safety.

Each medication has an interval in which the treatment should be administered. This interval ranges from daily to multiple weeks. In current practices, only daily or two-day interval medication is administered in the weekends since that is unavoidable. For longer intervals it is not desirable to treat these patients during the weekends, as costs for personnel are higher.

For the two specialisms oncology and cardiology, complete data from the past two years is available. For medication from specialism 'other' that is administered by other organisations, such as home care and commercial care organisations, only the number of patients is available. The characteristics of the medication that is administered is not available. Therefore, reasonable assumptions are made about the interval range and visit duration. Table 3 provides an overview of the medication per specialism.

In total, the oncology department visited 669 patients in 2019, with a total travel time of 236 hours (Isala Oncology Department, 2020). The average travel time per visit thereby is 21 minutes and 10 seconds. In Section 5, we will introduce a base case instance with which we can compare the average travel time per visit measured in 2019 with the performance of the developed model and solving methods in Section 6.

Specialism	**Patients per year**	**Interval range (days)**	**Visit duration range (minutes)**	**Average admissions/appointments per patient**
Oncology	120	3 - 30	25 - 90	6.63
Cardiology	451	1 - 7	20 – 110	3.46
Other	295	1 – 14	20 – 40	4

Table 3: Medication data per care specialism

5.2.2. Geographical information

To model accurate and real-life travel times, information about the location of patients is important. Since using street addresses is privacy-wise not acceptable, we reside to using postal codes. By converting postal codes to coordinates of the centre point of the postal code area, we can model travel times between postal code areas, and between postal code areas and the hospital. Travel times between coordinates are retrieved by using an API that is able to calculate driving times (by car) between coordinates (Bing Maps, 2021). We are only interested in travel times, as travel distances and Euclidian distances are too much influenced by traffic and the characteristics of the route (city and rural areas feature different average driving speeds).

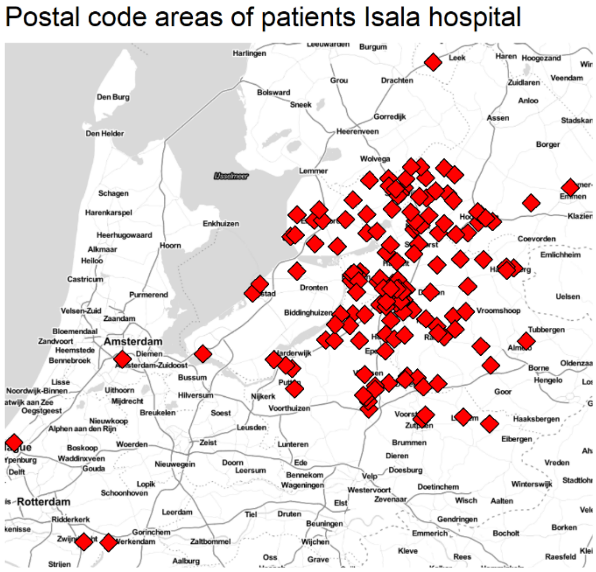

Figure 4: Postal code areas of patients that visit Isala hospital. Note that the geographical location is based on only the four digit postal code, for example postal code 1234 XX will be converted to the centre point coordinate of the 1234 area.

A drawback of only using postal code areas versus using street addresses is that the travel time for two patients in the same postal code area is zero. Therefore, a minimum travel time of five minutes is set for patients with the same location.

Figure 4 shows the postal code areas of all patients that receive care from Isala over the past two years. As expected, the postal code areas are centred around the city of Zwolle, the main location of Isala.

5.3. Experiments

We experiment with standard base case scenarios to assess the performance of the developed heuristics versus solving the problem exactly (if possible). In Sections 5.3.1 to 5.3.6 we will introduce the experiment instances derived from the business questions from Section 5.1.

Experiment instances are executed by using the instances as input for the greedy heuristic and ALNS algorithm implemented in Python and the ILP model implemented in AIMMS with CPLEX 20.1. The results of experiments will be presented in Section 6.

To test the performance of the algorithms compared to exact solving, we construct multiple test instances. The instances are increasing in complexity; more nurses and patients means that more combinations are possible and thereby adding to the complexity of the model. The instances feature a randomly generated treatment and travel time picked from a uniform distribution in a predetermined range. Each patient randomly receives a care frequency in a uniformly distributed predetermined range. The skills required for a patient is randomly picked from a uniform distribution. Each nurse has a shift from 8:00h to 17:00h, with a lunch break of 30 minutes. A nurse has therefore 480 minutes of working time available per day. Nurses each have one skill, and of each skill has at least one (in case of instance 1 and 2) or 2 (in case of instance 3) nurses are available. For the weekends we assume that for each skill, one nurse is available from 8:00h to 17:00h.

Instance number	**Number of nurses**	**Number of patients**	**Visit duration range**	**Number of different skills**	**Schedule length in days**	**Travel time range**	**Care frequency range**
1	2	10	20 – 60	2	7	1 – 30	1 – 14
2	3	15	20 – 60	2	7	1 – 30	1 – 14
3	3	30	20 – 60	2	7	1 – 30	1 – 14

Table 4: Standard experiment instances for performance evaluation

To determine the best starting temperature T, α and L for the ALNS algorithm, we use instance 3 as this instance contains enough patients to form a challenging problem instance. The standard stopping temperature T_{stop} is set at 0.1.

Starting temperature T_{start}	$\boldsymbol{\alpha}$	$\boldsymbol{L}$	**Performance (total travel time)**	**Runtime (s)**
50	0.05	500	425	28.2
50	0.025		399	61.3
50	0.01		382	166.4
50	**0.005**		**362**	**324.7**
25	0.05		429	27.3
25	0.025		429	49.4
25	0.01		402	125.8
25	0.005		399	252.5
15	0.05		460	21.9
15	0.025		452	45.4
15	0.01		461	95.1
15	0.005		438	202.4
10	0.05		479	16.9
10	0.025		492	33.7
10	0.01		467	85.2
10	0.005		473	147.2
50	0.05	750	386	43
50	0.025		390	99.5
50	0.01		389	230.4
50	0.005		371	452.7
50	0.05	1000	405	56.8
50	0.025		377	117.2
50	0.01		370	300.9
50	0.005		369	558.3

Table 5: ALNS parameters and results for instance 3

The experiments in Table 5 show that a starting temperature $T_{start} = 50$ and $\alpha = 0.005$ yields the best performance with a Markov chain length L of 500, while not having the longest runtime of all experiments. We expect that by running the algorithm longer, results will increase, however as visible in Table 5, that is not the case. For example, the experiments with a Markov chain length of 1000 do not perform better than the one with Markov chain length 500. A reason for this may be the randomness in both the construction and ALNS heuristic causing performance differences in each run of the algorithm. The runtime of around five minutes for the experiment with $T_{start} = 50$, $\alpha = 0.005$ and $L = 500$ is within a reasonable time frame and relatively low compared to exactly solving the problem, as shown in Section 6.1. Therefore, we use $T_{start} = 50$ and $\alpha = 0.005$ (and Markov chain length $L = 500$) for the remainder of our experiments.

For the experiments considering the questions from Section 5.1, we first develop a base case on which we will base the relevant experiments per topic. The base case is based on the medication and patient data from the medication at home patient of the oncology specialty. Furthermore, the location data is based on the location data introduced in Section 5.2.

Instance number	**Number of nurses**	**Number of patients**	**Visit duration range**	**Number of different skills**	**Schedule length in days**	**Travel time/distance range**	**Care frequency range**
4	2	20	25 - 90	1	7	Max 30 kilometres from hospital	3-30

Table 6: Base case data based on oncology specialism

5.3.1. Increasing number of patients

To examine the effect of more patients in the system, we develop three experiments that are based on instance 4, but increasingly feature more patients. To make sure there are enough resources available, we introduce an extra nurse, thus totalling three nurses. All other parameters are equal to instance 4. The experiments are shown in Table 7.

Instance number	**Number of nurses**	**Number of patients**	**Visit duration range**	**Number of different skills**	**Schedule length in days**	**Travel distance range**	**Care frequency range**
5	3	**30**	25 - 90	1	7	Max 30 kilometres from hospital	3-30
6	3	**45**					
7	3	**60**					

Table 7: Experiment Instances for increasing patients

5.3.2. Higher care frequency

The care frequency of the instance 4 are very dispersed. Therefore, two experiment instances are developed with higher care frequencies. The care frequencies are randomly picked from a uniform distribution in a predetermined care frequency range. Obviously, a higher care frequency should lead to more appointments and more intensive resource use.

Instance number	**Number of nurses**	**Number of patients**	**Visit duration range**	**Number of different skills**	**Schedule length in days**	**Travel distance range**	**Care frequency range**
8	3	30	25 - 90	1	7	Max 30 kilometres from hospital	1-14
9							1-7

Table 8: Overview of experiment instances with higher care frequency

5.3.3. Increasing travel time

To determine the effects of a higher travel time, we develop four experiments. The first of four experiments feature a maximum travel time of 20 minutes, increasing to 30 and 40 minutes in the next experiment. The last of four experiment instances feature no maximum travel distance. In practice, there are not many patients that live on more than 40 minutes of travel from the hospital, so we do not expect much difference between the third and last experiment. Instead of using distance, as Isala hospital is currently using, travel time is a much more consistent parameter than driving distance, as the average speed of travel differs per route. Other parameters are based on instance 6 (Table 7). Table 9 provides an overview of the four experiment instances. Figure 5 provides an overview of the locations and the travel time from the location to the hospital.

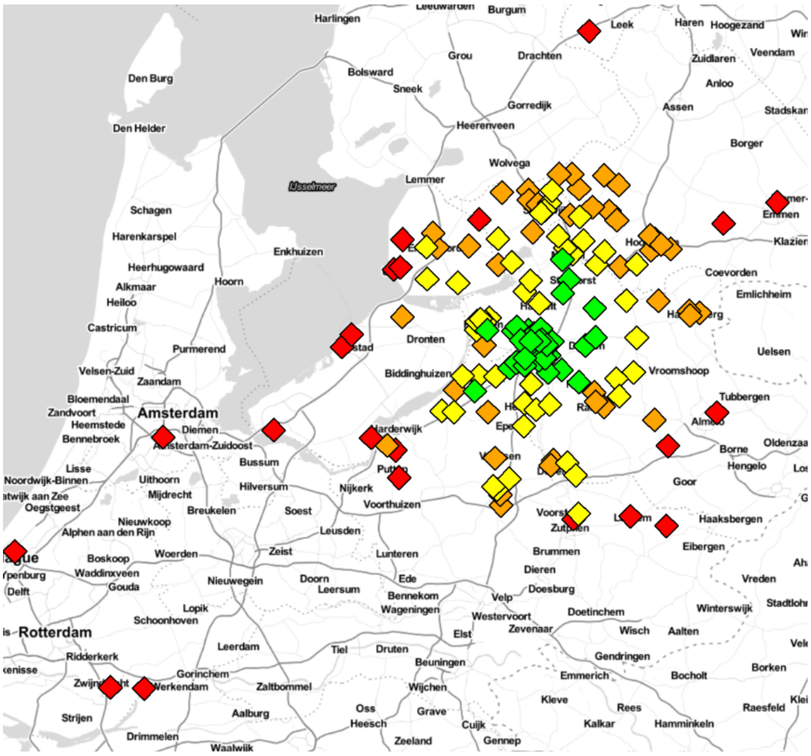

Figure 5: Overview of the patient locations. In red, locations with a travel time of more than 40 minutes from the hospital, in orange locations between 30 and 40 minutes, in yellow between 20 and 30 minutes and in green below 20 minutes.

Instance number	Number of nurses	Number of patients	Visit duration range	Number of different skills	Schedule length in days	Travel time	Care frequency range
10	3	45	25 - 90	1	7	**Max 20 min**	3-30
11						**Max 30 min**	
12						**Max 40 min**	
13						**No maximum**	

Table 9: Experiment instances for increased maximum travel time

5.3.4. Increasing variety of skills

The instances already presented in this section only feature one type of medication/skill. With more types of medication administered, nurses are only specialized in certain types of medication. Therefore, we introduce two experiments with multiple skills and nurses with multiple skills.. All other parameters are based on experiment instance 6. Instance 14 features two types of skills, with nurse 1 having skill 1, nurse 2 having skill 2 and nurse 3 having both nurse skill 1 and 2. Instance 15 features three types of skills, with nurse 1 having skill 1, nurse 2 having skill 2 and nurse 3 having skills 1, 2 and 3. The type of skill required at a patient is picked randomly from a uniform distribution.

Instance number	Number of nurses	Number of patients	Visit duration range	Number of skills	Schedule length in days	Travel time	Care frequency range
14	3	45	25 - 90	2	7	Max 30km	3-30
15				3			

Table 10: Experiment instances with more different skills

5.3.5. Longer planning horizon

The earlier discussed instances all feature a planning horizon of one week (seven days). Since the developed model can generate schedules for longer planning horizons too, we are interested in the effects on travel time if a longer planning horizon is introduced. We again base our experiments on instance 6 and use a planning horizon of 10 and 14 days for the experiments. In practice, creating a schedule with the same planning horizon as these instances may not be useful, as the access of new patients may require new scheduling.

Instance number	Number of nurses	Number of patients	Visit duration range	Number of different skills	Schedule length in days	Travel time	Care frequency range
16	3	45	25 - 90	1	10	Max 30km	3-30
17					14		

Table 11: Experiment instances with longer planning horizon

5.3.6. Combined experiments

The experiment instances from Section 5.3.1 to Section 5.3.5 are only based on the change of one parameter. However, combined effects may take place when two or more parameters are changed in a given instance. Therefore, five instances are developed where two parameters are changed. The developed instances are shown in Table 12 below. We consider an average number of patients (as derived from instance 6) for instances 18, 19 and 20. Instance 18 features no maximum on the travel time from hospital to patient and three different type of skills. Instance 19 has a limit of 20 minutes on the travel time from hospital to patient and features three different type of skills. Instance 20 features a longer planning horizon in combination with three types of skills. Instance 21 only deals with 30 patients, but these patients feature a care frequency picked from a uniform distribution between one and seven days. Instance 21 features a maximum travel time from hospital to patient of 20 minutes, while instance 22 has the same patient characteristics but without a limit on the travel time from hospital to patient.

Instance number	Number of nurses	Number of patients	Visit duration range	Number of different skills	Schedule length in days	Travel time	Care frequency range
18	3	45	25 - 90	3	7	No maximum	4-30
19					7	Max 20 min	
20					14	Max 30 **km**	
21		30		1	7	Max 20 min	1-7
22					7	No maximum	

Table 12: Combined experiments

6. Results

In this section, the results of the presented experiments in Section 5.3 are discussed and Section 6.8 will elaborate on the behaviour of the ALNS algorithm during execution. Table 13 shows an overview of the results for all experiment instances. Due to the varying care frequency of patients causing total visits in the total schedule to be varying, we opt for using average travel time per visit as main key performance indicator.

Instance number	CPLEX ILP solution	CPLEX ILP computation time (s)	CPLEX integrality gap	ALNS solution	ALNS computation time (s)	Greedy Heuristic Solution	Greedy Heuristic computation time (s)	Total visits	Average travel time per visit (best result, min:sec)	Average travel time per nurse (best result)
1	194	0.19	0%	198	164.4	344	0.1	15	12:56	97
2	311	996.2	0%	336	232.1	546	0.1	27	11:31	104
3	286	2400*	24%	375	291.3	687	0.1	45	6:22	95
4	280	2400*	29.7%	294	226.2	379	0.1	20	14:00	140
5	515	2400*	45.5%	462	339.8	654	0.1	30	15:24	154
6	No sol.	2400*	NA	666	372.6	907	0.2	45	14:48	222
7	No sol.	2400*	NA	773	426.1	1123	0.2	60	12:53	258
8	No sol.	2400*	NA	679	285.7	928	0.1	39	17:25	226
9	No sol.	3600*	NA	1204	521	1600	0.2	69	17:27	401
10	No sol.	3600*	NA	532	396.4	711	0.2	45	11:49	177
11	No sol.	3600*	NA	652	328.3	904	0.2	45	14:29	217
12	No sol.	3600*	NA	851	366.1	1028	0.2	45	18:54	284
13	No sol.	3600*	NA	877	298.1	1074	0.1	45	19:29	292
14	No sol.	3600*	NA	886	443.1	1195	0.2	45	19:41	295
15	No sol.	3600*	NA	872	310.7	1235	0.2	45	19:23	294
16	No sol.	3600*	NA	1290	583.1	1537	0.2	66	19:33	430
17	No sol.	3600*	NA	1319	633.6	2198	0.1	80	16:29	440
18	No sol.	3600*	NA	898	244.2	1235	0.2	45	19:58	299
19	No sol.	3600*	NA	522	388.8	732	0.2	45	11:36	174
20	No sol.	3600*	NA	1269	476	2167	0.2	76	16:42	423
21	No sol.	3600*	NA	754	372.5	956	0.2	71	10:37	251
22	No sol.	3600*	NA	1418	366	1852	0.2	65	21:49	473

*Table 13: Overview of results of all experiment instances. * cut-off time specified*

6.1. Standard performance experiments

Instances 1 to 3 are the standard experiment instances to test the performance of the developed solution algorithms. The results show that the ALNS algorithm is capable of providing solutions that perform close to the solutions found by solving the ILP model with the CPLEX solver. The increasing complexity, which can be observed from the total number of visits, results in higher computational times needed and as can be observed in instance 3 may result in an ILP solution with a fairly large integrality gap. Meanwhile, the ALNS algorithm is, in case of instance 3, still possible to attain reasonable results in a fraction of computation time.

The performance of the greedy algorithm proves to be significantly higher than the ALNS algorithm (and ILP solution), with the benefit of having a very low computation time that does not increase with increased complexity of the experiment instances.

6.2. The base case

The results of instance 4 show that the average travel time per visit for the base case is 14 minutes and 21 seconds, which is a large improvement over the 21 minutes and 9 seconds that the oncology department measured in 2019. The moderate complexity of the problem enables the CPLEX solver to find a result within the specified cut-off time of 2400 seconds. The ALNS algorithm proves again to be attaining close performance in less computation time. As concluded in the previous section, the greedy algorithm proves to perform far less than the other two solving methods.

6.3. Increasing patients

Increasing the amount of patients that have to be visited has a positive effect on the average travel time per visit, as the results for instance 5 to 7 show. The average travel time for instance 7 is almost two minutes lower compared to instance 5. The decrease in travel time can be explained by the fact that nurses can travel more efficient routes. With more patients to be visited, the probability that another patient is close to a patient, is higher than with a lower amount of patients.

The increase in patients results in an increase in complexity, owing to the extra visits that have to be scheduled. As result, the cut-off time of 2400 seconds does not result in a solution by CPLEX for instance 6 and 7. For the ALNS and greedy algorithm, the computation time only marginally increases. As discussed in previous sections, the ALNS proves to attain reasonable results in a fraction of the computation time compared to the CPLEX solver.

6.4. Care frequency

An increased care frequency results in a higher average travel time per visit, as can be observed by the results of instance 8 and 9. The total visits for instance 8 and 9 increase significantly compared to instance 6. An explanation for the increase in average travel time per visit can be that, since patients have to be visited more often, the possibilities for creating efficient routes are less. As discussed in the previous section, this effect could be decreased by introducing more patients and thereby making the patient group more heterogenous. Of course, more patients or visits always increases the total travel time.

6.5. Travel times

Experiment instance 10 to 13 show that increasing the maximum allowed travel time from hospital to patient causes the average travel time per visit to increase significantly, as well as the total travel time. This effect is unsurprising and can be explained by nurses having to travel further and patients being more scattered over the service region (as Figure 5 already showed). However, the increases in average travel time are significant compared to the previous experiments, with a difference of 7 minutes and 40 seconds between instance 10, with patient locations at maximum 20 minutes from the hospital, and instance 13, with patients locations at no maximum travel time. Furthermore, the increase of the instance with no maximum travel time compared to the instance with 40 minutes maximum travel time, is small, owing to the existence of only a small number of locations outside the 40 minutes range (Figure 5).

6.6. More variety of skills

Instance 14 and 15 show that increasing skills causes a moderate increase of average travel time per visit. Furthermore, in instance 15 the resulting schedule shows that most workload is placed upon nurse 3, which is expected as this nurse can serve all types of patients and therefore, in most cases, the most efficient route can be created with this nurse. In a real-world situation with nurses that have multiple skills, it may be therefore be necessary to introduce workload balancing in similar situations (although these may have a negative effect on the average travel time per visit).

6.7. Longer planning horizons

Experiment instance 16 and 7 show that a longer planning horizon results in more visits in the resulting schedule. Furthermore, the longer planning horizon features a moderate increase in average travel time per visit compared to instance 6. This may be due to the fact that only a handful of patients require extra appointments and therefore the routes that are created for visiting these patients may prove to be less efficient..

6.8. Combination of factors

The results for experiment instance 18 and 19 show that the maximum travel time from patient to hospital has a significant effect on the average travel time per visit, in line with the discussed results in Section 6.5. The results for instance 20 shows that a longer planning horizon in combination with two skills instead of one, has a comparable average travel time per visit as instance 17, which has a longer planning horizon but does only feature one type of skill. The results for instance 21 and 22 show that again a high maximum travel time from hospital to patient causes high average travel time per visit, however this time also with patients that have a high frequency of visits. However, in instance 21, where only patients are considered located within 20 minutes of driving from the hospital, the average travel time is lower than instance 10, which featured the same 20 minutes maximum but less frequent visits of the same patients. A possible cause maybe that with lower travel times between patients, the higher frequency of visiting the same patients does not necessarily influence the optimal routes as much as it does when the travel times between patients are higher. Instance 22 shows that having no maximum on travel time and high frequency visits of patients results in a considerably higher average travel time per visit compared to instance 13, which featured no maximum on travel time but far less frequent patient visits, confirming our previous statement.

6.9. ALNS performance and operator performance

To demonstrate how the ALNS heuristic optimizes the solution for experiment instance 6, Figure 6 shows the development of the performance per iteration. Figure 6 clearly shows the converging of the heuristic to an optimized solution, accepting worse solutions in the beginning and slowly accepting less worse performing solutions as the temperature parameter T drops.

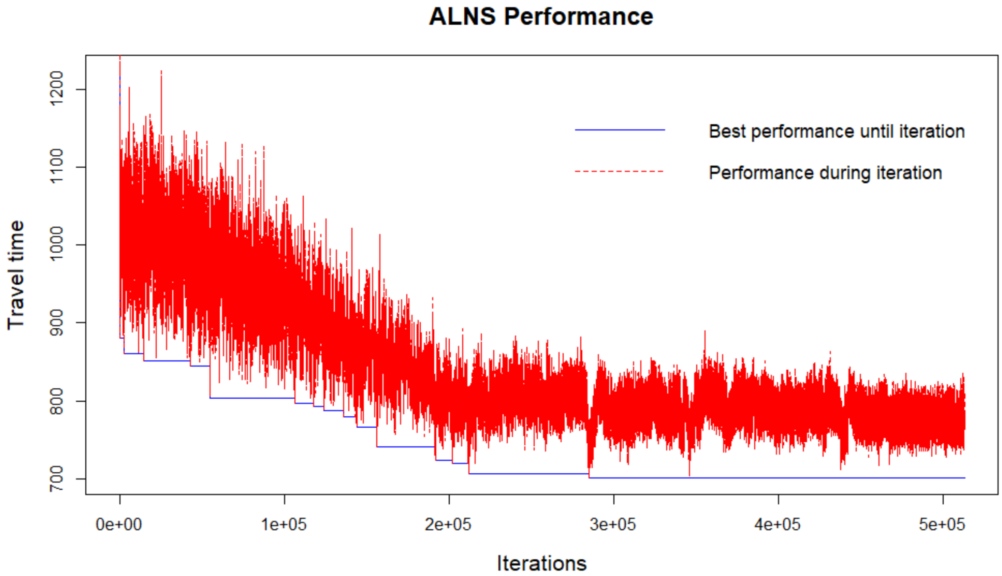

Figure 6: ALNS performance per iteration for instance 6.

The selection of insertion and removal operators is executed through a distribution based on scores of the operators. In the same experiment as Figure 6, we tracked the score of each insertion and removal operator at each temperature change. When a better solution is found than the current solution, the operator score gains the set reward $\sigma = 100$. Figure 7 shows the operator scores over time. The random removal operator outperforms the biggest gap removal operator over time. A cause may be that removing the visit with the most travel time has been already very optimized that it is hard to find a better solution. The insertion operators' performances diverges through time, with the best pair insertion operator outperforming the random insertion operator. From Figure 7 we would conclude that using an operator based on randomness performs worse when the solution is further optimized. Furthermore, based on Figure 7, using other operators next to randomness-based operators is useful.

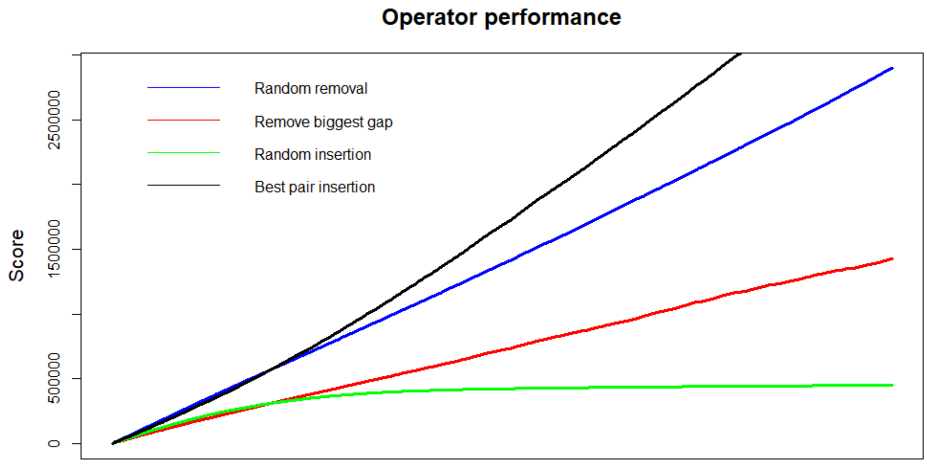

Figure 7: Operator performance during execution of ALNS algorithm for instance 6.

7. Conclusions & Further research

7.1. Conclusions

This paper proposes an optimization model for medication at home routing and planning in the context of a hospital providing parental medication to patients. A case study is conducted at Isala hospital considering the effects of changing patient characteristics on the total travel time needed to serve all patients. We develop a ILP model capable of constructing and optimizing routing and planning of medication at home patient visiting. To the best of the author's knowledge, no specific research has been done to medication at home practices and routing and planning optimization. Furthermore, we introduce an adaptive large neighbourhood search approach which provides reasonable solution performance in short computation time by showing that, for small instances, the ALNS results range from -10% to 31% compared to solutions generated by CPLEX. Next to this neighbourhood search approach, we introduce a greedy heuristic capable of providing solutions in computational time less than one second and attaining performance that is 19% to 83% worse compared to optimal solutions found by the ALNS algorithm. The complexity of the ILP model with larger instances causes high computational times for CPLEX when solving and in most instances no solution can be found within the specified cut-off time. The large computational time needed for CPLEX solving makes the ALNS heuristic attractive in practical situations where computational time should be limited while still providing decent performance.

We develop several experiment instances derived from the case study at Isala hospital. The base case instance, based on data from the oncology department, shows that the average travel time per visit by using the model decreases with more than 30% compared to the measured performance in 2019. The results show that the maximum allowed time or distance for the travel time from hospital to patient has the largest effect on the average travel time per visit in the schedule of patient visits. Increasing the number of patients to be treated causes a significant decrease in the average travel time needed per visit. Furthermore, we show that a higher care frequency, where patient receive more visits over a fixed period, has a moderate negative effect on the average travel time per visit. Introducing multiple skills and nurses that can handle multiple skills leads to a moderate increase of average travel time per visit, with the workload skewed to nurses with multiple skills rather than nurses with only one skill. Through experiments with the adjustment of multiple-parameters, we show that a high allowed maximum travel time from hospital to patient in combination with frequent visits of patients lead to a significant increase in average travel time per visit. On the other hand, high frequent visits of patients living close the hospital results in more optimized routes than optimizing planning with patients that do not have to be visited frequently and are located close to the hospital.

7.2. Further Research

Extensions and adaptions to the constructed ILP model might be addressed easily by introducing new constraints and/or parameters. In the HHCRSP literature, preference, time windows and synchronization are examples of typical constraints in HHCSRP models. Furthermore, stochastic parameters can be introduced to examine the robustness of the created schedules. Parameters that could be stochastic include travel time and visit times.

With the current constructed model, making two sequential schedules may get conflicting results, as constraint 9 rounds down the number of visits required in the planning horizon. When scheduling sequentially, this may result in too few visits for patients over the two planning horizons added together, as shown in Section 3.2. A possible solution may be to save the number of visits in one planning horizon and use that information in the construction of a new planning.

In the current model we assume that all information is known beforehand. However, in practice, information arrives at separate moments, e.g., new patients arrive each (working) day. A possible research direction may be to develop a model that can deal with rolling planning horizons, by 'feeding' new patients to the model at the moment they are known, or at specific moments in time, for example every day.

The ALNS heuristic has proven to work well in the experiment instances treated in this research. The analysis of the operator scores (Figure 7) showed that the operators show different behaviour during execution of the algorithm. The ALNS performance can be increased by adding additional removal and insertion operators that provide better performance or comparable performance in less time. An example would be to use geographical clustering or removing geographical outliers from existing routes. Another example would be to make a distinction in patients with low or high care frequency, as An et al. (2012) show that patients with a higher care frequency have more influence on the schedule performance than patients with a low care frequency.

In the experiments executed in this research the standard degree of destruction is one. However, further research may look into the effects of increasing the degree of destruction and the possible effects on performance and computation time.

The current location data used is based on four digit postal codes. Further research could include a more detailed analysis by using full postal codes (four digits + two letters in the Dutch system) or full street addresses. By adding more detail to the location data, driving times can be modelled more accurate.

The constructed model optimizes on total travel time but may be adapted to also include costs. For example, fixed costs of nurses/vehicles can be included, as we describe in Section 3.2. While the current model can optimize routes and schedules, the model does not support decisions as to whether a patient should be eligible for medication at home or not (currently we assume that decision is already made beforehand based on medical/practical criteria). A future research direction would be to incorporate decisions whether to treat patients at home or at the hospital and the relation with the efficiency of routes. For example, a patient that has negative effects on the efficiency may be better treated at the hospital to improve efficiency. Of course, the medical aspect of operations should be considered, as can never by the single criterion to decide which patient to treat at home and which patient should not be treated at home.

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Appendix 1. Search strategy literature

Search keywords used

Database	**Keywords/Search terms**	**Results**	**After initial selection**	**After reading abstract**
Scopus	TITLE-ABS-KEY (home AND medication) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "ECON"))	62	2	
	TITLE-ABS-KEY (home AND healthcare AND medication) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "ECON"))	43	1	1
	TITLE-ABS-KEY (home AND healthcare AND routing) AND PUBYEAR > 2009	115	24	21
	TITLE-ABS-KEY (home AND care AND scheduling) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "MATH") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "ECON"))	151	28	25
Web of Science	TOPIC: (home healthcare routing). Refined by: WEB OF SCIENCE CATEGORIES: (OPERATIONS RESEARCH MANAGEMENT SCIENCE) Timespan: 2010-2012. Indexes: SCI-EXPANDENDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.	20	17	9
	TOPIC: (home healthcare) Refined by: WEB OF SCIENCE CATEGORIES: (OPERATIONS RESEARCH MANAGEMENT SCIENCE)Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2010-2021	68	25	14
	Total (*including duplicates)*	**459**	**97**	**70**

Table 14: Overview of the literature search strategy

Selection for taxonomy based on articles that have the answer YES on the following questions:

Is the article NOT a literature review?

Is the article containing some form of a mathematical model?

Is the problem containing some sort of traveling to patients (a routing component)?

Is the article available through the literature databases available at the University of Twente?

Total selection of articles: 32 in table, selected from a total of 70 articles.

Appendix 2. Literature Overview

Article	Model type	Objective	Dynamic (D) / Static (S)	PR	NQ	TW	SY	WR	ST	CS	Solving method
(Ait Haddadene et al., 2019)	VRPTW-SP (Synchronization and precedence)	TRC + PRF	S	X		X					Non-Dominated Sorting Genetic Algorithm
(An et al., 2012)	Periodic VRP (P-VRP)	TT	S	X							Two-phase heuristics
(Bard et al., 2013)	VRPTW (MDVRPTW)	TC	S	X	X	X		X			Exact/Heuristics
(Baumann, 2018)	VRPTW	PRF + DE + TT + TWE	S	X		X		X			Exact
(Bazirha et al., 2020)	HHCRSP (Home healthcare routing and scheduling problem) adapted from VRPTW	TC	S	X	X	X			X		Genetic Algorithm
(Belhor et al., 2020)	HHCRSP	TWS	S	X							Exact
(Braekers et al., 2016)	HHCRSP	TC + PRF	S	X	X	X		X			Metaheuristics (Multi-directional local search and Large Neighbourhood Search)
(Castaño & Velasco, 2020)	HHCRSP	TC, D	S		X	X					Benders approach
(Chen et al., 2017)	Orienteering (team) problem – Multiperiod HHCSP	TR	S	X	X	X		X	X		Exact/Langrage relaxation
(Cinar et al., 2021)	Prioritized Home Healthcare Problem	TT, TR	S			X		X			Successive single period heuristic/ALNS/Exact

Article	Model type	Objective	Dynamic (D) / Static (S)	PR	NQ	TW	SY	WR	ST	CS	Solving method / methodology
(Demirbilek et al., 2019)	Dynamic VRP	PV	D	X	X	X			X		Scenario based approach / Simulation
(Dengiz et al., 2019)	HHCRSP	T+D	S		X	X					Exact
(Di Mascolo et al., 2017)	--	TT	S		X	X		X			Algorithm
(H. H. H. H. H. Doulabi, 2020)	VRPS (synchronized visits)	TC, TRC	S				X		X	X	Two-stage model / L shaped algorithm
(Euchi et al., 2020)	HHCRSP	D	S		X	X	X	X			Ant Colony System
(Heching et al., 2019)	VRPTW	PV	S	X	X	X	X	X			Benders approach
(Hewitt et al., 2016)	Consistent VRP (ConVRP)		S	X		X					Exact
(Hiermann et al., 2015)	VRPTW	*Multiple with weights(13 total)*	S	X	X	X		X		X	VNS/SA/Memetic Algorithm
(Laesanklang & Landa-Silva, 2017)	HHCRSP	*Multiple (4) worker balance*	S		X	X		X			Decomposition

Article	Model type	Objective	Dynamic (D) / Static (S)	PR	NQ	TW	SY	WR	ST	CS	Solving method
(Liu et al., 2019)	MDVRPTW	TC + penalty for clients not served acc. to planning	S			X			X		Branch-and-price algorithm
(Moussavi et al., 2019)	VRPTW	D	S	X				X			Exact/Heuristic
(Nasir & Kuo, 2020)	HHCRSP	RC, TRC	S			X	X	X			Hybrid Genetic Algorithm
(Nikzad et al., 2021)	SDDARP (Stochastic districting, staff dimensioning assignment routing problem)	Multiple cost factors	S		X	X		X	X		Several algorithms
(Quintanilla et al., 2020)	asymmetric TSP	TT	S		X		X				GRASP algorithm
(Riazi et al., 2014)	HHCRSP	D	S		X	X		X			Gossip algorithm
(Y. F. Shao, J. F. Bard, & A. I. Jarrah, 2012)	HHCRSP	TC, TT, D	S	X	X	X		X			Greedy randomized adaptive search (two-stage
(Shiri et al., 2020)	HHCRSP	Multiple cost indicators	S			X		X	X		Mulvey approach
(Taieb et al., 2019)	VRPTW	TT, PRF	S	X		X	X				Exact (Cplex)

Article	**Model type**	**Objective**	**Dynamic (D) / Static (S)**	**PR**	**NQ**	**TW**	**SY**	**WR**	**ST**	**CS**	**Solving method**
(Veenstra et al., 2018)	VRP+FL (facility location)	TRC	S					X			Hybrid VNS
(Wang et al., 2020)	HHCRSP	*Multiple Satisfaction indicators*	S			X		X			(Hybrid) Whale Optimization Algorithm
(Zhan & Wan, 2018)	RASTA(Routing and appointment scheduling with team assignment)	TC	S			X		X	X		Tabu Search
(Zhang et al., 2019)	HHCRSP	*Multiple (combination of adhering to constraints and feasibility)*	S	X	X	X		X			Simulated Annealing

Table 15: Overview of the studied literature

Legend:
PR = Preferences

Objective functions:

- TC = Total Cost
- RC = Route assignment cost
- TRC = Travel cost
- D = Distance
- PRF = Preference
- DE = Different Employees

- TT = Travel Time
- TWE = Total Waiting time employees
- TWS = Total weighted starting Time
- TR = Total Reward
- PV = Patients Visited (or served)
- T= Tardiness

NQ = Nurse qualification

TW = Time Windows

SY = Synchronization

WR = Work regulations

ST = Stochastic

CS = Case study

HHCRSP = Home Health Care Routing and Scheduling problem

VRPTW = Vehicle Routing Problem with Time Windows

VRPS = Vehicle Routing Problem with Synchronization

Static and Dynamic: We define static as all input information known beforehand and dynamic as not all input information known beforehand.

Appendix 3. Overview of experiment instances

Instance number	Number of nurses	Number of patients	Visit duration range	Number of different skills	Schedule length in days	Travel time/distance range	Care frequency range
1	2	10	20 – 60	2	7	1 – 30	1 – 14
2	3	15	20 – 60	2		1 – 30	1 – 14
3	3	30	20 – 60	2		1 – 30	1 – 14
4	2	20	25 - 90	1		Max 30 kilometres from hospital	3-30
5	3	30				Max 30 kilometres from hospital	3-30
6		45					
7		60					
8		30				Max 30 kilometres from hospital	1-14
9							1-7
10		45				Max 20 min	3-30
11						Max 30 min	
12						Max 40 min	
13						No maximum	
14				2		Max 30km	3-30
15				3			
16				1	10		3-30
17					14		
18				3	7	No maximum	4-30
19						Max 20 min	
20					14	Max 30 km	
21		30		1	7	Max 20 min	1-7
22						No maximum	