Designing a criteria-based appointment planning method for outpatient clinics using stochastic optimization.

A case study at the Internal Medicine Department of Isala Hospitals

Graduation Thesis

Industrial Engineering and Management

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November 2023

UNIVERSITY OF TWENTE.

isala

Master Thesis Industrial Engineering and Management

Specialisation: Production and Logistics Management

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Management summary

Value driven appointment scheduling

The internal medicine outpatient clinic of Isala runs into its capacity borders and will cross these borders in the future if nothing changes in the organization of care. To deal with this problem the clinic wants to introduce *value driven appointment scheduling* at the internal medicine department. This research is about how the value-driven appointment scheduling method should look like, what the benefits are and how to implement the method. The focus of this research lies at the nephrology department, since this department treats a lot of chronic patients, this patient group is suitable for implementing the value-driven appointment scheduling method.

We first want to know what the impact of introducing value-driven appointment scheduling is.

As shown in Figure 1, based on data of 2022, we identified that 17% of the Neprhology-CKD patients and 7% of the Nephrology-NCKD patients can be treated in primary care Therefore, we did a data study in which we found answer to the question how big the potential of the proposed method is. This is done by looking in the data of 2022, an see how many patients an appointment at the nephrology department of Isala had, while there was no medical reason for the appointment, based on established criteria. The outcomes of the data analysis are shown in Figure 1. In total, we say that only 57% of the appointments has a direct medical reason for appointment, for 25% the need for an appointment should be determined based on a patient file review, and 18% of the appointment has no medical reason to take place. The results are presented in a dashboard.

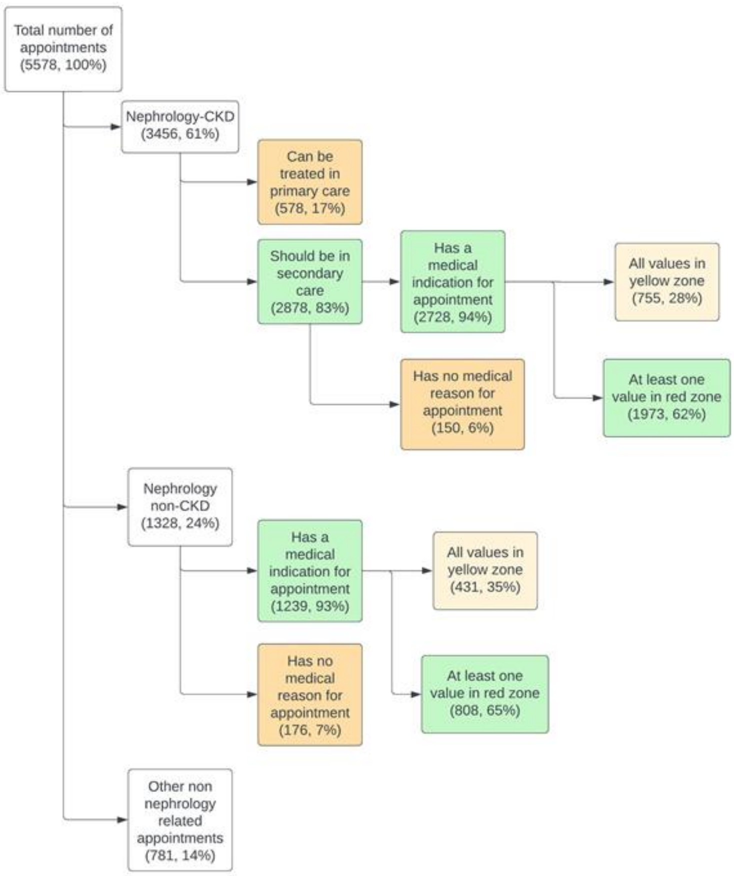


Figure 1: Outcomes of the data analysis.

The next step is to find out what the impact of the method is on the blueprints of the nephrologists. Therefore, we conducted a literature study to find the best way to optimize blueprint schedules, based on uncertain demands. From the literature study, we concluded that we should formulate a stochastic Mixed Integer Linear Program that has as output the optimal blueprint.

Mathematical model
To find the optimal blueprint, we formulated a Mixed Integer Linear Program. This is a 2-stage stochastic program. The first stage decision is the number of slots opened in the blueprint for each patient group and resource, and the second stage decisions are the number of overtime and idle time slots opened for each demand scenario. Input for this model are the demand distributions of the patient groups and the capacity of the resources, in this case the nephrologists. The model is able to deal with a maximum percentage of overtime and penalizes the overshoot of this percentage. Output of the model is the blueprint containing the number of slots opened for each patient group and resource, and the amount of overtime and idle time for each scenario. Sample Average Approximation has been applied to deal with the stochasticity of the model and creating a robust solution as possible.

Experiments and results
Various experiments have been executed test the model both on theoretical and practical side. Theoretical, we tested the model on the effect of certain parameter values. We calculated the Value of Stochastic Solution and the Expected Value of Perfect Information. We also tested the effect of the maximum percentage of overtime on the blueprint and amount of over- and idle time. On the practical side, we saw that the introduced method has an effect on the amount of overtime and needed number of slots for each patient type, compared to the current situation. Furthermore, we saw that the model functions as expected when adding weights to the objective, in which we balance the amount of overtime and idle time. Finally, we tested the model for different increased demand scenarios. In this experiment, we saw that the nephrologists can handle up to an increase of 20% of demand with the value-driven appointment scheduling method, while currently they are running into the capacity borders.

Conclusion and discussion
The contribution of this research is twofold. First, we showed that there is a large potential for introducing value-driven appointment scheduling, by creating a data dashboard, we showed that only 57% of the appointments at the nephrology department have a direct medical reason for it. So, if we prevent the other appointments from taking place by introducing criteria-based appointment scheduling, we increase the capacity significantly. Second, we showed that we use a stochastic MILP to create the optimal blueprint for the nephrology department. We also see that the value-driven appointment scheduling method leads to a decrease in the needed number of slots in the blueprint, and in the amount of overtime.

We recommend Isala to start implement the value-driven appointment scheduling method, but also to investigate the patient perspective of this method. In this research, we only looked at the medical criteria for needing an appointment, but it is strongly recommended to also do research on what the patient perspective of this method is and what the influence of a patient-initiated appointment is.

Acknowledgments

This thesis on “Designing a criteria-based appointment scheduling method using stochastic modelling” concludes my student time and my time at the University of Twente. It is the final step towards my master’s degree in Industrial Engineering and Management.

I am thankful that I could perform my graduation project at Isala Zwolle. I have always been interested in healthcare, and doing by graduation project at this hospital gave a great insight in the world of healthcare and the complex processes involved here. I want to thank everyone at Isala who was involved in this research for their massive help. Especially, I want to thank Ton Roelofs and Joan Doornebal, who guided me during the research project. Ton and Joan were always available for questions and helped me a lot during the whole research process.

With no doubt, I want to thank my UT supervisors Gréanne Maan-Leeftink and Sebastian Rachuba. I enjoyed our meetings, and you always were very helpful keeping the focus in the right direction. Your insights, feedback and tips really guided me towards the end product as it is right now, thank you for that.

Finally, I want to thank my family, friends and girlfriend for the constant support during my studies and this research project. Special thanks to Jur and Stan, for your insights, feedback and ideas during this research project. I have learned a lot these years, and I look forward to what the future will bring!

Ruben Klaas

Zwolle, November 2023

1. Introduction

This chapter discusses the problem context and research plan of this project, conducted at Isala. In this chapter, a first introduction to the project is given. In Section 1.1, the background is discussed, in Section 1.2 the problem context is given and in Section 1.3, the research plan is given.

1.1 Background

This research is conducted at the internal medicine department of Isala Hospitals. For the remainder of this research, we will refer to the Isala hospital group as 'Isala'. Isala is a large regional hospital, with five locations in Zwolle, Meppel, Steenwijk, Kampen, and Heerde. Isala has around 7000 employees, 1250 available beds, and a yearly turnover of around 824 million euros [1].

The internal medicine department employs 37 internists, which makes it one of the largest internal medicine departments in the Netherlands. The department is built up out of two sub-departments, general internal medicine and oncology/hematology. General internal medicine has the following focus areas:

- Acute medicine
- Endocrinology/diabetes
- Infection diseases
- Elderly medicine
- Nephrology
- Vascular medicine

As the name suggests, the focus areas of the oncology/hematology sub-department are patients with oncology and hematology-related diseases. Besides patients with diseases related to one of the focus areas, the internal medicine department also treats patients with diseases related to general internal medicine.

1.1.1 Research Motivation

In this subsection, the motivation for this research is described. According to the Integral Care Agreement, the accessibility of care in the Netherlands is under pressure [2]. The number of people with chronic diseases and multiple diseases at the same time will increase. In addition, the number of elderly people compared to the number of working citizens increases. This will cause a fast increase in the need for care [2]. In line with the integral care agreement, the Internal Medicine outpatient clinic of Isala runs into its capacity limits. Therefore, the way care is planned at the Isala outpatient clinic needs to be changed. An important aspect of this change is the switch to value-driven care, provided by the internal medicine outpatient clinic. Value-driven care is a more and more used concept in healthcare. Porter [3]described the need to switch from traditional care to value-driven care, where value is defined as achieving the best outcomes at the lowest costs. Currently, healthcare is not focused on efficiency. But with the rise of people needing care and lack of capacity, the healthcare sector has steps to make regarding efficiency. Value-driven care is a key concept in making healthcare more efficient. Research should be done on how to arrange and design this value-driven care.

1.2 Problem context

In this section, the problem context of this research will be described. First, we will describe the action problem. Second, we will describe the problem identification. Third, the core problem is given and last, the research goal is explained.

1.2.1 Action problem

In this subsection, the action problem of this research will be described. As said, the internal medicine outpatient clinic of Isala runs into its capacity borders and will cross these borders in the future if nothing changes in the organization of care. As described in Heerkens & Van Winden [4], anything or any situation that is not how you want it to be is an action problem. It is the discrepancy between norm and reality, as perceived by the problem owner. In this case, the problem owner is the management of the internal medicine department within Isala. The norm is that there is enough capacity to treat all patients coming to the outpatient internal medicine clinic, but the reality is that this capacity is not there.

1.2.2 Problem identification

To identify and understand the causes of the action problem, a problem cluster is made. The problem cluster is shown in Figure 2. Input for this problem cluster is an observation study, which consisted of interviews and follow-along sessions with internists, secretaries, and planners at the internal medicine outpatient clinic. These sessions gave an introduction to the current way of working and how things go at the outpatient clinic.

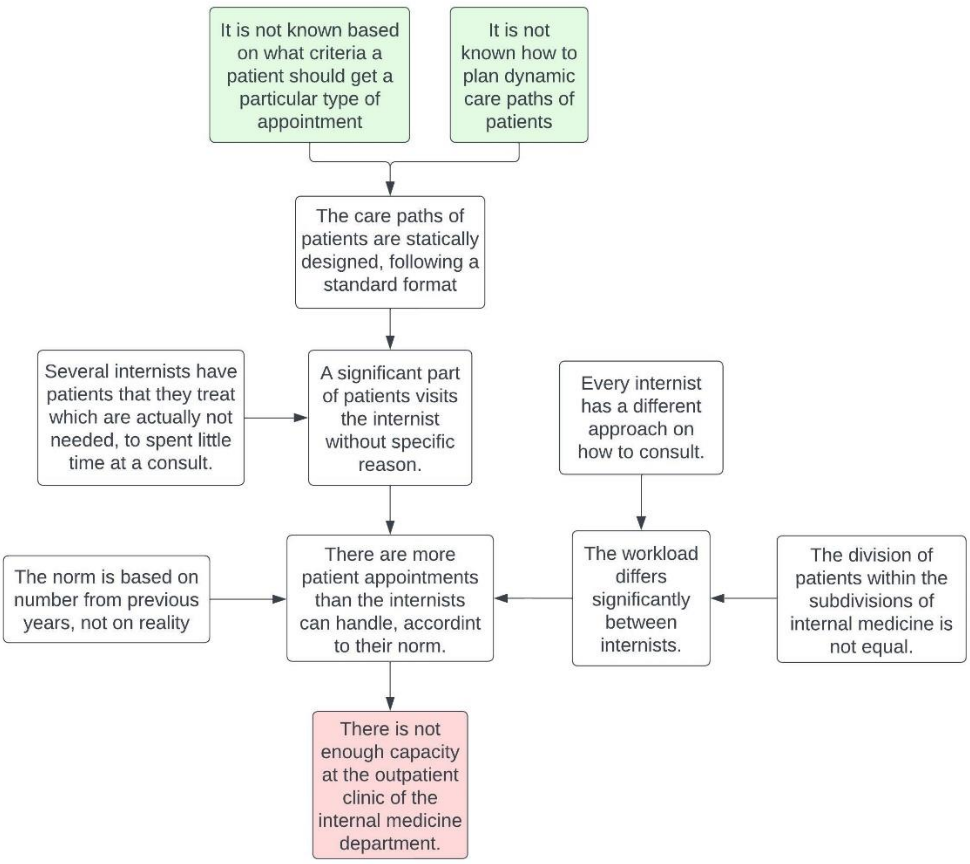


Figure 2: Problem cluster of the assignment at the internal medicine department of Isala.

When we look at the action problem 'There is not enough capacity at the outpatient clinic of the internal medicine department', this problem is caused by more patient appointments being planned than the internists can handle, according to their norm. If an internist works full time, their norm states that they should have 17 consultation hours per week, besides other tasks. When looking at the actual hours spent on consulting, compared to what the norm states, almost every internist spends more time on consulting than his or her norm states.

This problem is caused by multiple other problems. First, the norm for the number of consulting hours is based on the numbers of previous years and not on the number of consulting hours in reality. This problem is currently solved by a capacity test that is done by the Center of Improvement and Innovation of the hospital. Second, the workload division between the different internists differs significantly. This is mainly caused by the fact that the division of patients within the focus group of internal medicine is not equal. Another student is currently doing research into this problem. Of course, every internist has his or her style and way of working when doing a consultation hour. This also means every internist has another workload, based on the way of working he or she has. Third, the problem of having more patient appointments than the internists can handle is also caused by a significant part of patients visiting an internist without a specific reason. During the observation study, it became clear that several appointments with a specialist only consisted of the patient saying that everything went well, and the specialist saying that all blood- and urine values are correct. Therefore, these consults do not add medical value to the treatment of the patient and could be done in another way, or not at all.

The above-described problem has two main causes. One of them is that some internists have patients they treat, who do not need that much treatment, but these patients are still in the patient register of this internist because they are relatively ‘easy to treat’. These patients are in some way used to save time, which can be spent on a patient who needs more than the scheduled time for the consult. This is not ideal and should be prevented, but the processes are organized in such a way that it is needed apparently. The other cause is that the care paths of patients follow a static design and format. Right now, four types of appointments exist. These types of appointments, with their corresponding duration, are shown in Table 1.

Table 1: Types of appointments within the Internal Medicine outpatient clinic

Type	Scheduled time (minutes)	Description
New patient (NP)	30	Physical consult for the first visit of a patient to an internist, declarable
Control patient (CP)	15	Physical consult for a patient being under the supervision of an internist, declarable
Telephone consult long (TCLang)	15	Phone consultation which is declarable at the health insurer
Telephone consult short (TCKort)	5	Phone consultation which is not declarable at the health insurer

In Table 1, we see that three types of consultation can be declared at the health insurer. Notably, there is no option to have a video call with a patient, while this option is used in practice. In addition, the duration of consultations is fixed and is not based on certain criteria. This makes it hard to schedule an appointment based on the needs of a patient, and therefore it is likely that a patient gets the wrong type of appointment scheduled.

As indicated earlier, patients follow a static care path when visiting the internal medicine outpatient clinic. The durations and frequency of appointments are fixed. Two causes of the problem that care paths are statically designed are that it is not known based on what criteria a patient should get a particular type of appointment and that it is not known how to plan dynamic care paths for patients within the outpatient clinic of internal medicine. We define the dynamic care path as a care path that is not fixed in advance. Based on certain criteria, it can be determined whether a patient needs an appointment or not.

1.2.3 Core problem

In this subsection, the selection of the core problem is explained. According to Heerkens & Van Winden [4], a problem is a possible core problem if it has no cause by itself. As can be seen in the problem cluster (Figure 2), several problems exist which do not have a cause by itself. First, a possible core problem is that the norm is based on numbers from previous years, not on reality. The fact is that at the moment of writing, a capacity test is executed, in which the actual capacity, and with that the actual norm of appointment hours are determined. Second, several internists have patients they treat who are not needed, to spend less time on their consult. This is something that has to do with the organization of care within the outpatient clinic. Therefore, this problem is not taken into account in this research. Third, a possible core problem is that every internist has a different approach to how to consult. It is not up to the researchers to determine in which way an internist should do his or her consultation hours. Therefore, this problem is not taken into account in this research. Fourth, the division of patients within the focus groups of internal medicine is not equal. This could be a possible core problem. Another student is working on this problem, at the same time as this research is executed. Therefore, this problem is not the core problem of this research.

The fifth and sixth possible core problems are that it is not known based on which criteria a patient should get a particular type of appointment and it is not known how to plan dynamic care paths for patients. These are problems that do not have a cause by themselves and have the potential to be solved within this research. Therefore, these problems are selected as core problems.

1.2.4 Research goal

As described in the research motivation, the outpatient clinic wants and needs to provide value-driven care for its patients. Currently, not all care adds value to the care of the patient. This research is set up to find a way to switch from 'a patient has *an* appointment, unless…' to 'a patient has *no* appointment, unless…', to prevent patients from coming to the outpatient clinic without specific reason. The goal of this research is therefore to:

> *Minimize the non-value-adding appointments for patients at the internal medicine outpatient clinic, while ensuring the quality of care.*

The road on how to reach this goal will be further described in the research plan.

1.3 Research plan

In this section, the research plan of this research is discussed. First, we will describe and explain the research questions that should be answered. Second, the scope of this research will be discussed.

1.3.1 Research questions

In this subsection, the research questions and sub-research questions are discussed. For each question, it is explained why this question should be answered to find a solution to the core problems.

The main research question of this research is:

> *How can appointment planning at the internal medicine outpatient clinic become value-driven?*

To answer this question, the following research questions need to be answered:

1. **What does the current planning process at the outpatient clinic look like?**

To improve the planning process at the outpatient clinic, we first need to understand what the current processes within the clinic look like. Isala indicated that the current processes are static and that their wish is to have dynamic care paths based on medical criteria for the patients that can profit from this. Therefore, we need to know in what way the current process is a static care path. Furthermore, Isala wants to provide value-driven care. To work on this development, it is important to understand the term value-driven care and understand what the definition of value is.

2. **What is the potential effect of using health conditions to determine the type of appointment?**
   a. **Which health conditions should lead to a certain type of appointment?**
   b. **How many unnecessary appointments can be prevented based on these health conditions?**

The second research question will be answered to determine the potential of using certain health conditions to determine the type of appointment of a patient. To determine, we first need to know which values, for example, the kidney function, determine the type of appointment a patient gets. When we know these medical values, we look into data at which patients have had a physical appointment and had blood- or urine values that did not indicate to come to the outpatient clinic. This indicates how many appointments could be saved, theoretically.

3. What information does the literature provide about optimal outpatient clinic blueprint scheduling?
   a. **What can we use regarding dynamic care paths?**
   b. **How can dynamic care paths be planned?**

A literature study will be performed to answer the second research question. This literature study will focus on outpatient clinic planning and what models are available to use. Also, this study investigated what dynamic care paths are and how they can be planned within the process. From this literature, a broader study can be executed to find models for dynamic patient planning at an outpatient clinic.

4. **How can we model the planning of dynamic care paths within the outpatient clinic?**

Dynamic care paths require a completely other way of planning than static care paths. Now, the outpatient clinic has static care paths, and therefore, the planners can plan patients for a relatively long period, say three months in advance. When transferring to dynamic care paths, where for example, a patient visits an internist based on the outcomes of a questionnaire two weeks before the appointment, the planners also know only two weeks before the appointment which patients they should schedule and which patients not. This requires another type of planning. A mathematical model will be created which determines the best design and planning strategy for the new appointment planning. This model will test several ways of planning and for example, how many patients should be planned at one appointment slot.

5. **How can dynamic appointment planning be implemented at the internal medicine outpatient clinic?**

This question is answered to see how the new way of having appointments can be implemented in the internal medicine outpatient clinic of Isala Zwolle. This way of having appointments should be merged with the current way of having appointments, because several other types of patients that come to a certain internist exist, and these appointments are scheduled traditionally.

6. **What conclusions and recommendations can be drawn from this research?**

Finally, conclusions should be drawn, and recommendations should be made from this research. What can we advise the internal medicine outpatient clinic?

1.3.2 Scope

This research is conducted at the internal medicine department of the Isala Hospital. Within this department, several focus groups exist. The focus of this research is first on the nephrology group of the department. This focus group is at the moment of writing working on a new carepath for patients with chronic kidney injury in which this study can also be used. Besides that, every focus group within the internal medicine department treats different kinds of patients, which also require a different type of care. Therefore, we should first focus on one division, and when possible, expand the method found for this focus group to other focus groups. Nevertheless, we should keep in mind that this approach requires a generic solution type for all focus groups, to be able to expand.

2. Context analysis

In this chapter, the context analysis for conducting the research will be given. The goal of this chapter is to answer the following research question:

What is the potential effect of using health conditions to determine the type of appointment?

This research question has two sub-research questions namely: “Which health conditions should lead to a certain type of appointment?” And “How many appointments can be prevented based on these health conditions?” By answering these questions, we see what the effect of criteria-based appointment scheduling can be on the nephrology department of Isala.

2.1 Current planning method

In this section, the current appointment planning method for patients in the internal medicine department at Isala is described. Based on a full-time contract, an internist should have seventeen consultation hours per week. Several ancillary activities are subtracted from these 17 hours, which results in ten to twelve consultation hours per specialist per week, based on a full-time contract. These ten to twelve hours are open for consultations with patients.

Mainly four types of consultations are used for appointment planning. A New patient appointment, which takes half an hour and is meant for patients that visit an internist for the first time. Control patient appointment, which takes fifteen minutes and is meant for a follow-up appointment. A long phone consultation hour, which also takes fifteen minutes and is used parallel with a physical consultation hour, and a short phone consultation, which takes five minutes, and is meant to quickly discuss things with a patient, for example, the results of a blood test.

Appointments are planned mostly by the secretaries of the sub-departments of the internal medicine department. Each specialist has a pre-defined weekly schedule where the types of appointments are pre-set to be scheduled. We will refer to this pre-defined schedule as the blueprint for the rest of this report. The ratio between each type of appointment is defined once defined in history, and all blueprints are built upon the historic determination.

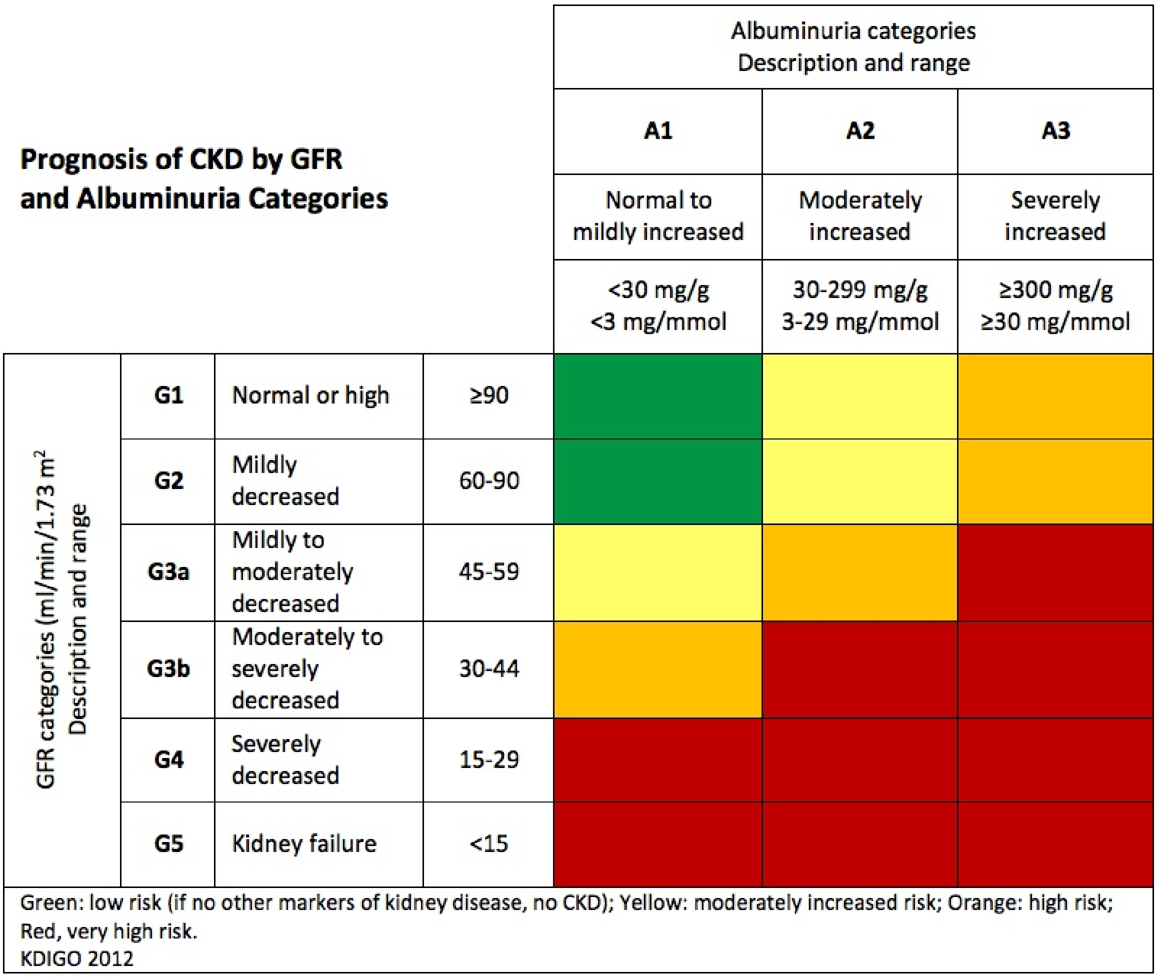
From interviews with planners and secretaries, it turned out that they try to stick to the blueprint, but in many cases, this is not doable. For example, it often happens that there are more patients for a follow-up appointment than patients coming for the first time. In that case, a slot for a new patient is filled up with two follow-up patients.

Currently, the appointments are scheduled according to the first come first serve (FCFS) principle. When an appointment should be planned, the first available slot available at the right specialist is found and the appointment is placed in that time slot.

The current planning method is not designed to deal with short-term or even walk-in-based appointment planning. Therefore, in this research, a planning method, based on literature is developed to deal with patients only having an appointment based on certain criteria.

2.2 Chronic Kidney Disease

The focus group for this research is the group with chronic kidney disease, treated by the nephrology section of the Internal medicine department. Chronic kidney disease (CKD) is defined as the presence of an abnormal kidney function (eGFR) and an abnormal marker of kidney disease, for at least three months [5]. An important marker is the albumin-creatinine ratio (ACR). Dependent on these markers and the eGFR, different risk categories exist. In Figure 3, the risk table is given for the eGFR and ACR values.



Prognosis of CKD by GFR and Albuminuria Categories

				Albuminuria categories Description and range		
				A1	A2	A3
				Normal to mildly increased	Moderately increased	Severely increased
				<30 mg/g <3 mg/mmol	30-299 mg/g 3-29 mg/mmol	≥300 mg/g ≥30 mg/mmol
GFR categories (ml/min/1.73 m²) Description and range	G1	Normal or high	≥90			
	G2	Mildly decreased	60-90			
	G3a	Mildly to moderately decreased	45-59			
	G3b	Moderately to severely decreased	30-44			
	G4	Severely decreased	15-29			
	G5	Kidney failure	<15			

Green: low risk (if no other markers of kidney disease, no CKD); Yellow: moderately increased risk; Orange: high risk; Red, very high risk.
KDIGO 2012

Figure 3: Chronic Kidney Disease risk table [6]

In Figure 3, albuminuria stands for the ACR marker. We see that for the eGFR, six risk levels exist, and for the ACR three. The typicality of CKD is that disorders arise only when the kidneys have lost a big part of their function. This makes it important to measure and monitor people with CKD closely.

2.2.1 Criteria for an Appointment

In this subsection, we will discuss the medical criteria based on which to determine whether a consultation is needed or not. With these criteria, we look into data on how many consultations have taken place while there was no medical indication to have one.

Together with nephrologists, the criteria that indicate the need for an appointment have been determined. For patients with CKD, the following indicators are important to keep track of:

- eGFR
- ACR
- PCR
- Blood pressure
- Hemoglobin
- Ferritin
- Potassium
- Calcium

- Phosphate
- PTH
- Sodium

A distinction can be made between indicators based on which can be determined whether a patient suffers from CKD and values that can be affected by CKD. Indicators based on which can be determined whether a patient suffers from CKD are the eGFR, ACR, and PCR. eGFR stands for estimated glomerular filtration rate and is a measurement of how well your kidneys are working [7]. ACR stands for albumin-creatinine ratio. The ACR says something about the amount of albumin in the urine. Albumin is the most common type of protein in urine [8]. Persistently increased protein in the urine is the principal marker of kidney damage and acts as a sensitive marker for among others, CKD. Together with the ACR, PCR indicates the albuminuria categories in CKD, as shown in Figure 3. PCR stands for protein-creatinine ratio and indicates the amount of all proteins in urine. The PCR is also an important indicator for kidney diseases.

The eGFR, ACR, and PCR give input to determine the kidney function of a patient. The table in Figure 3 indicates the kidney function of a patient and whether a patient should be seen by a nephrologist or that the patient can be treated by a General Practitioner (GP).

If someone is diagnosed with CKD, this can affect several other functions of the human body. To keep track of the effects of CKD on the rest of the body of the patient, several other blood values are monitored while the patient is under the supervision of a medical specialist. These indicators are blood pressure, hemoglobin, ferritin, potassium, calcium, phosphate, PTH, and sodium. Besides these values, the eGFR, ACR, and PCR are monitored during the supervision of a medical specialist. The values of these indicators determine whether a patient needs consultation or not.

Together with a nephrologist, the critical values of each of the indicators are determined. A distinction is made for values that indicate a check of the patient file, after which a nephrologist can decide to have a consultation with a patient, and values that directly indicate a consult is needed.

The criteria mentioned above indicate whether it is needed for a patient to have an appointment with a specialist or not. The values of these criteria can be divided into groups. If a value does not indicate an appointment at all, it is in the *green zone.* If a value indicates to have a look at the patient file, it is in the *yellow zone*. If a value gives a direct reason to have an appointment, it is in the *red zone.*

In Table 2, the values and indication in which zone they are given. This division is verified with one of the nephrologists and discussed and approved by the nephrologists working at Isala.

Table 2: Criteria values

Criterium	Green zone	Yellow zone	Red zone
Progression eGFR	<15% compared to previous measure	-	≥15% compared to previous measure
ACR	<3,0	3-30	≥30
PCR	<0,15	0,15-0,5	≥0,5
Syst. Blood pressure	101-130	131-140	≥141 or ≤100
Potassium	3,0-3,4	3,5-5,5	<3,0 or >5,5
Calcium	2,20-2,65	2,10-2,19	<2,10 or >2,65
Phosphate	<1,50	1,50-1,80	>1,80
PTH	7,0-35,0	<7,0 >35,0	-
Bicarbonate	≥20	18-19,9	<18,0
Natrium	135-145	130-134	<130 or >140
Anemia	Man: ≥8,5 Woman: ≥8,5		

2.3 Data analysis

In this section, the data analysis we made is described. First, we will describe how we got the data and what the data requirements are, second, we will describe how we transferred the data to make it usable for our analysis, and third, the actual data analysis will be discussed.

2.3.1 Data export

In this data analysis, we wanted to know which CKD patients had a consultation with a nephrologist or nursing specialist at the internal medicine department in 2022, while having no medical indication to have a consultation. To do so, we needed appointment and laboratory data, retrieved from the ERP system of Isala. Isala uses a data transfer program to transfer the data from the ERP into usable comma-separated values (CSV) files. In this program, a search string can be built up containing the requirements for the data needed. In our case, we needed data from patients diagnosed with CKD. This is specified in the data transfer program as patients who had at least two times an eGFR value lower than 60, or an ACR/PCR value that indicated for a consultation hour. We wanted to look at the year 2022 since this year is representative of other years and is not affected by for example COVID-related modifications in appointment types or appointments. Besides that, patients should have an eGFR measurement in 2022, otherwise, they probably do not have CKD. Also important to mention is that patients who do not want their data to be used in research are excluded from the search in this research, but since this percentage is really low (>0.1%), the effect on the outcomes of this research will be minimal.

Next, we wanted to know how many appointments each type of patient had. Therefore, we included every appointment the patient had in the period from the first of January 2021 till now. Later, we filtered on 2022, to only use the appointments in this year. For each indicator, we want to know all measurement values of all patients included in the data. Each measurement is valid for one year, so, therefore, every measurement from the first of January 2021 is included in the data. For the eGFR, we even needed more data than from this date. This is because a 25% decrease in eGFR over the last five years is also an indication for an appointment. Therefore, the eGFR measurement values from the first of January 2017 are included in the data set.

With this data set, we have information about how many and which type of appointments each patient had, and all required medical values known from these patients.

2.3.2 Data transformation

The data that comes out of the data transfer program of Isala cannot directly be used for our data analysis, since not all medical data is linked to the appointments. We first needed to transform several parts of the data to be able to make the analysis. The most important transformation was to link the most recent measurement values to each appointment. This is needed to determine whether a consultation should have taken place, the most recent data based on which decision can be made should be known. To do so, a Visual Basic (VBA) script has been written to link the most recent measurement values to the appointments. Furthermore, the progression of the eGFR value should be monitored. Therefore, it has been calculated whether the eGFR has decreased by more than 15%, compared to the previous measurement, and thus indicates to have a consultation. Also, the albuminuria classification has to be determined. To do so, the values of the ACR and PCR are combined to determine the albuminuria classification the patient had at the moment of the appointment.

With these data transformations, the dashboard can be made. The dashboard will be discussed in the next section.

2.3.3 Data loading

With the data retrieved from the data transfer program, the data can be loaded into a dashboard to analyze the number of appointments that are taking place while having no specific reason for it. The dashboard can be seen in Figure 4.

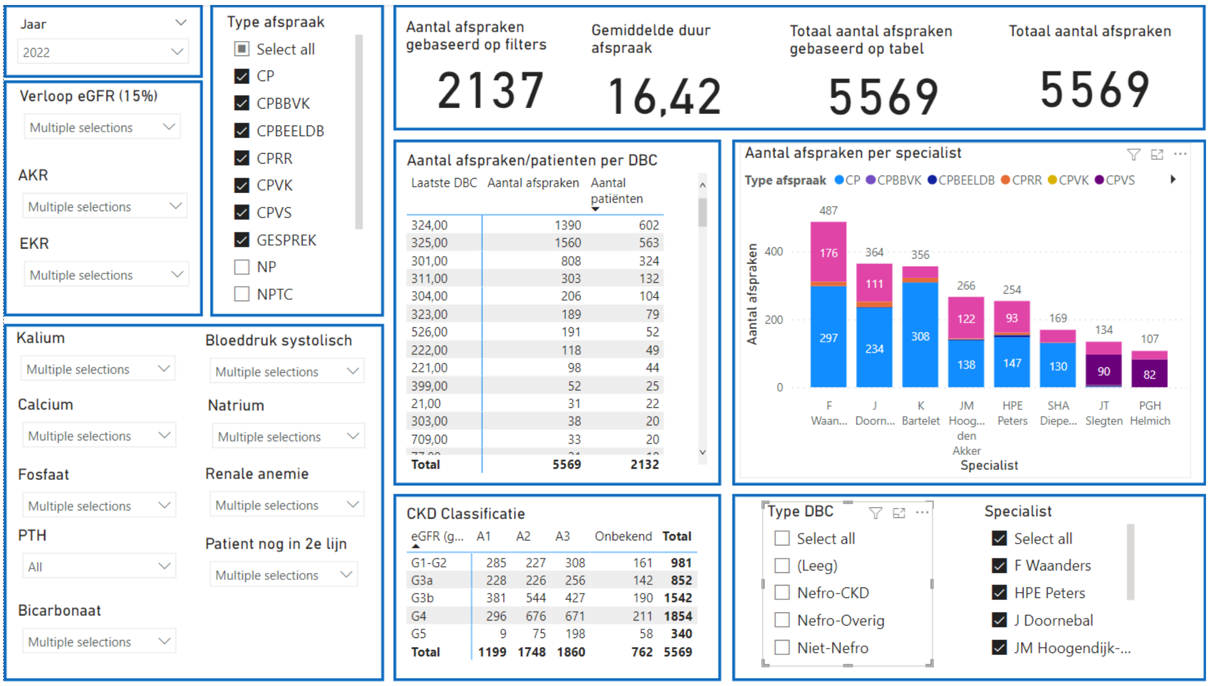


Figure 4: Data dashboard to see the potential of other planning techniques

In Figure 4, the dashboard can be seen. In the top left corner, we filter the data by year, in this case, we selected the year 2022. Below the year filter, the filter for the eGFR and ACR, and PCR (AKR and EKR in Dutch) are shown. For each filter, the categorized values can be selected. Below are the filters for eGFR, ACR, and PCR, the filters for the rest of the measurement values can be applied. In the center bottom, the type of DBC can be selected. DBC stands for *Diagnose behandel combinatie* or Diagnosis treatment combination. This is a classification of the diagnosis and treatment a patient's care fits in. Based on a DBC, the health insurer pays an amount of money for the care of the patient to the hospital. Three groups of DBCs can be separated. Patients with CKD (Nefro-CKD), patients with nephrology-related diseases, except CKD (Nefro-Overig), and patients with a disease not specifically for the nephrology specialism, like common internal medicine-related diseases. In the table called 'CKD classificatie', the same groups as in Figure 3 can be identified. Based on this table, the patients that had an appointment in secondary care, while having a CKD indication to be treated in primary care can be filtered out.

At the top, four numbers can be identified. The most left number, titled 'Aantal afspraken gebaseerd op filters' represents the number of appointments that took place, based on all filters used on the left of the dashboard. Next to that, the 'gemiddelde duur afspraak' calculated the average length of an appointment. The total number of appointments, based on the filters of the CKD classification table can be seen at the top right corner of the dashboard. This number shows the number of appointments based on the CKD risk classification filter. Finally, the number titled 'totaal aantal afspraken' represents the total number of appointments. This number is the total number of appointments that took place within the selected period.

2.3.4 Analysis of the Dashboard

In this section, the outcomes of the dashboard will be analyzed. To do so, different filter combinations have been applied to select the right group of patients. The outcomes from the dashboard are put in Figure 5, to get an overview of the division of patients having an appointment while having no medical indication for it.

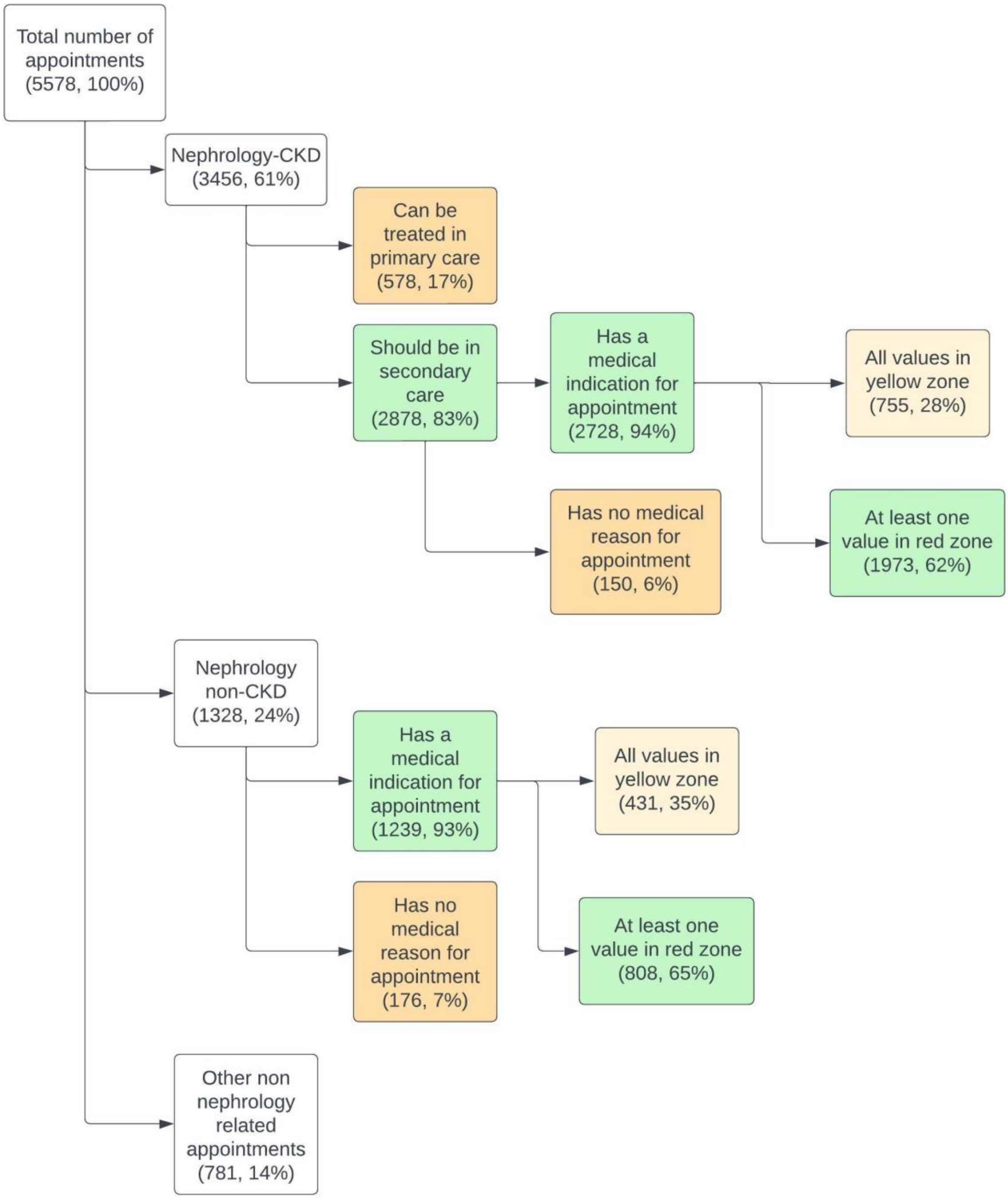


Figure 5: The division of appointments

In Figure 5, one can see that the total number of patients is split up into three groups, based on their DBC:

- Nephrology-CKD
- Nephrology-non-CKD
- Other non-nephrology-related appointment

Starting with the third group, this group is left out of the analysis. Since these patients visited a nephrologist without nephrology-related reasons, it is unknown whether their appointment took place with valid medical reasons or not. A closer look has been taken at the patients with CKD, and the patients with other nephrology-related diseases. Patients with CKD can be divided into patients allowed to be treated in primary care and patients who should be treated in secondary care. This is based on their eGFR and ACR values, and with Figure 3 their risk can be determined. It turns out that 578 of the 3456 appointments (17%) took place while a patient can be treated in primary care.

The second group should be treated in secondary care. For this group, we examined whether the medical criteria indicated for a patient file review or an appointment. 226 of the 3090 appointments (7%) took place while the criteria did not indicate it. When looking at the group that had a medical indication for an appointment, a distinction can be made between appointments where all criteria were in the *yellow zone* and appointments where at least one value was in the *red zone.* At 755 out of the 2728 (28%) appointments, all criteria values were in the yellow zone, which means 2181 of the 2864 appointments (72%) took place with at least one value directly indicating an appointment.

2.4 Conclusions

In this chapter, our main goal is to investigate what the potential is of implementing criteria-based appointment scheduling. In total, 4784 appointments took place in 2022 among nephrology patients. If the appointments without medical indication of all groups are added, it can be concluded that 904 (19%) appointments took place while there was no medical indication at all. On top of that, if all values in the yellow zone are added, it can be concluded that 1186 appointments (25%) took place while at least one value is in the yellow zone, and the others are in the green zone. For these appointments, the patient file should be inspected, after which can be determined whether an appointment is needed or not, or a digital appointment can take place. Finally, only 2781 of the 4784 (57%) appointments had a direct medical indication to have an appointment. This means that there is a large potential to improve the value-based planning approach, given the large portion of appointments that take place without medical indication for it.

3. Literature review

In this chapter, the literature review performed will be discussed. In the literature review, we answer the following question:

> *What information does the literature provide about outpatient clinic blueprint scheduling?*

This will be done by first looking at where this research is placed in the framework of Hans et al. [9]. After that, existing literature on blueprint scheduling will be discussed. In the last section, literature on stochastic modeling related to healthcare is discussed.

3.1 Positioning of this research

In this section, the positioning of this research in the field of OR in healthcare will be discussed. An important framework in this concept is the work of Hans et al. [9], who propose a generic framework for health care planning and control.

The framework consists of two parts; the managerial areas are the columns of the framework, and the hierarchical decompositions form the rows of the figure. The framework can be seen in Figure 6.

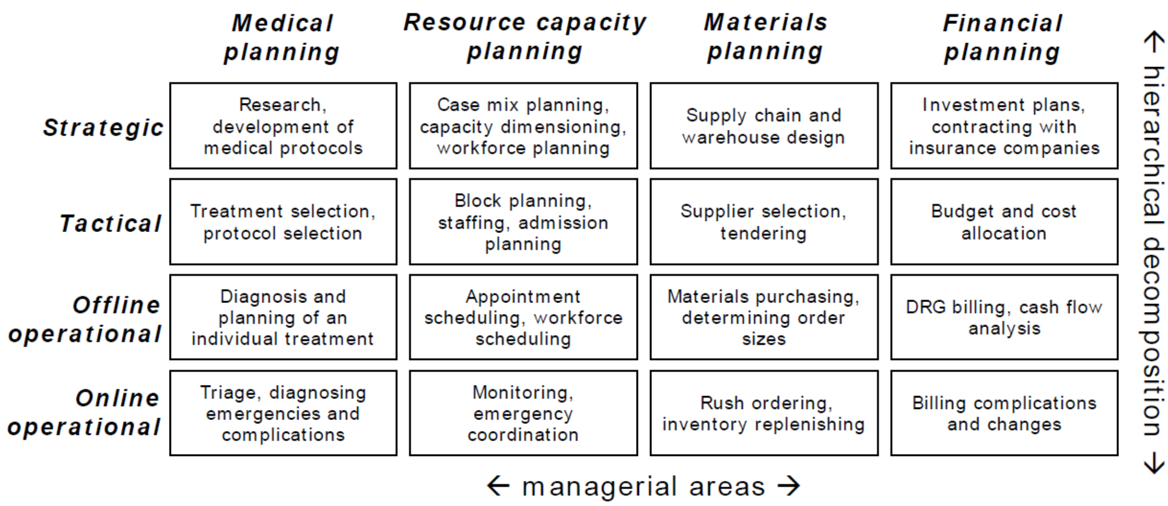


Figure 6: Framework for healthcare planning and control (derived from [9])

When taking a look at this research, and where to put it in the framework, this research fits in the resource planning area of management. This research concerns the capacity planning of the internists and nursing specialists of the internal medicine department at Isala. When looking at the hierarchical level of the framework, this research can be placed on the tactical level. This is because this research focuses on creating a blueprint schedule for the caregivers of the internal medicine department.

3.2 Increasing variability?

The goal of this research is to implement a value driven appointment scheduling method, by adding an extra step in the appointment scheduling process, namely the check whether an appointment is needed or not. This will probably increase the variability in patient demand. The question is how to deal with this variability. Therefore, we search for literature that describes this and can give us a direction for how to deal with this.

In the field of operations research, many analytical studies have been executed finding the optimal algorithm for appointment scheduling [10][11]. In these studies, the main source of variability is mostly the length of the appointment. Other sources of variability are the number of patients to be scheduled, presence of a medical specialist and breakdown of equipment[12]

Hopp and Spearman [13] are suggesting that after reducing variability by minimizing no-shows and last-minute cancellations, variability can be counterbalanced by the flexibility of patients and resources. Their idea is to reduce the effects of variability by adapting to the idea that patient demand might be flexible, and therefore also the capacity of resources should be flexible. For example, a medical specialist can spend unanticipated idle time by doing administrative work or other pending tasks. Implementing flexible production is also adapted by Toyota and other manufacturing facilities [14], [15].

Kuiper et al. [16] did a multiple case study in which they tested to work with more loose schedules. In Figure 7, we can see the models tested in the study. Most outpatient clinics work with the baseline scenario, in which the slots are planned tight, and all non-scheduled tasks have to be done outside the appointment hours.

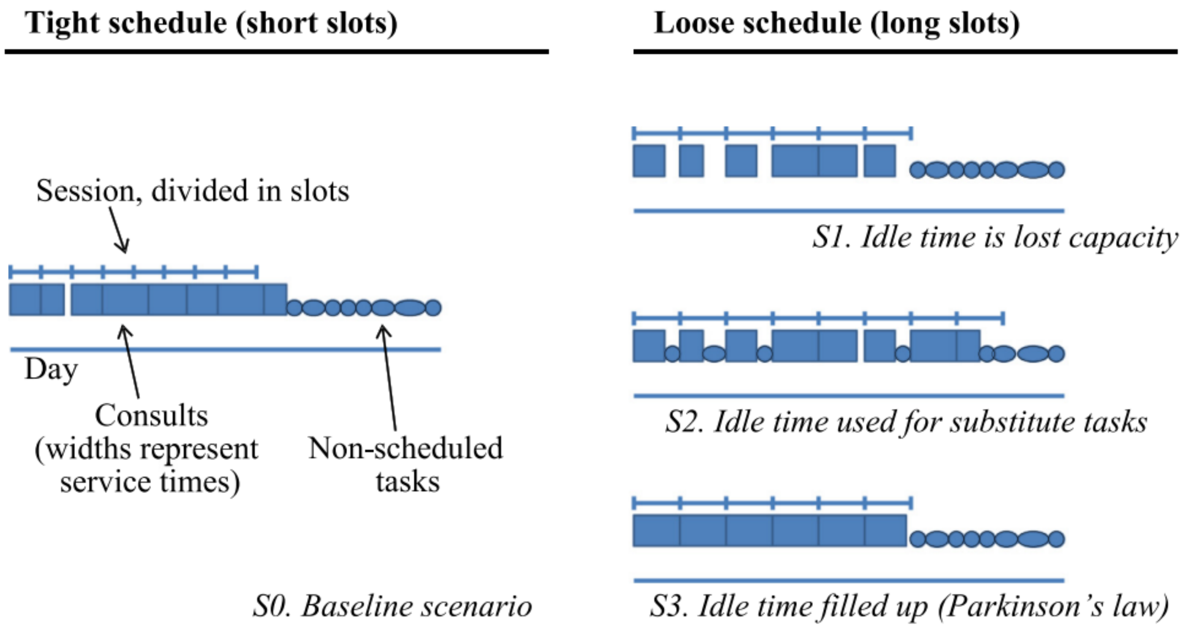


Figure 7: models tested by Kuiper et al.[16]

The most interesting model of Kuiper et al. [16] is S2, where the slots are planned more loose, and the idle time is used for substitute tasks. This is most applicable to our case, where we also have to deal with fluctuations in patient demand.

3.3 Blueprint scheduling

One of the goals of this research is to create an optimal blueprint schedule for the internists and nursing specialists of the internal medicine department of Isala. Therefore, a literature review has been done on the research done earlier on blueprint scheduling, especially in outpatient clinics, and with different patient types. This is done by first analysing the different types of blueprint there are available. When these are identified, we dive deeper into the most suitable blueprint for this study, to find out what the optimal way of blueprint scheduling for this research is. A technique that has been used for this is the snowballing technique. The outcomes of this review will be discussed in this subsection.

Healthcare planning and control is becoming increasingly popular since expenditures are rising and therefore healthcare organizations are forced to organize their processes more efficiently and effectively [9]. This also causes an increased interest in blueprint scheduling.

3.3.1 Types of Blueprints

In literature, different types of blueprints are discussed. The difference is mostly caused by the level of detail within the description of the blueprint.

Zomer [17] introduced a framework for blueprint classification. This framework consists of two dimensions. The first dimension is the level of detail of the blueprint. This aspect is important for choosing a blueprint since it has a major impact on the way of working [17]. The subcategories used in the framework are listed below:

- Percentages for patient types: This blueprint has the lowest level of detail. The blueprint only consists of the percentage of capacity assigned to a certain patient type.
- Block scheduling: The blueprint consists of blocks of patient types, with a start- and end time.
- Block scheduling with a number of patients: This blueprint also consists of blocks with patient types, but the number of patients to treat in each block is fixed.
- Slots filled with appointment types: The blueprint consists of slots with a start and end time and a specific patient type assigned to the slot. This is the most detailed blueprint.

The second dimension of the framework consists of the KPIs of a blueprint[17]. This means each blueprint is generated to have optimal values for a certain KPI. The KPIs discussed in Table 3 are used for the framework of Zomer. The framework is shown in Figure 8.

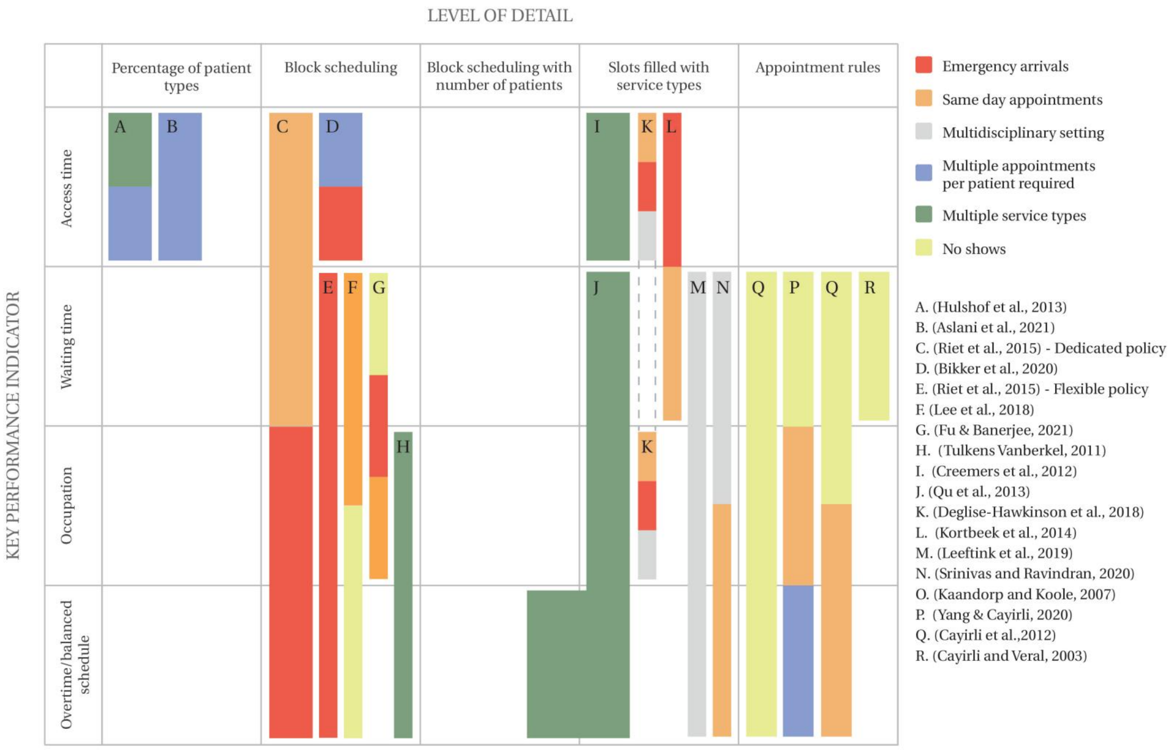


Figure 8: Blueprint framework, derived from [17]

In Figure 8, one can see that most research on blueprints has been done on the level of detail of block scheduling. Little research has been done on the 'percentage of patient types' blueprints. And on the 'Block scheduling with a number of patients' type of blueprints. More research has been done on the 'Slots filled with service types' type of blueprint and on applying different appointment rules. This research focuses on determining an amount of slots to open for a certain patient type, a more detailed type of the percentage of patient types blueprint discussed in Hulshof et al. [18] and Aslani et al. [19].

Hulshof et al. [18] made a model to determine the percentages of patient types the blueprint should consist of. The method they used is a Mixed Integer Linear Program (MILP), which is solved in AIMMS. The objective of this model is to minimize the number of patients waiting in a queue. Aslani et al. [19] developed a robust optimization model to create a blueprint that divides the patient groups over the blueprint. Aslani et al. [19] created a robust optimization model, not using demand distributions to base the optimal decision on. This is not possible for the problem of this thesis, since we want to create a model to use for the future, not knowing what the exact patient demand will be.

Nguyen et al.[20] wrote an extension to a previous paper[21], to include demand uncertainty by formulating a stochastic linear optimisation model. In this paper, they also used chance constraints to deal with uncertain parameters. A chance constraint makes sure that a certain probability is lower than a fixed value [20]. This can also be used for the model we create, since we want to ensure the overtime to be lower than a certain percentage. They first develop a deterministic model that finds the required capacity over a finite horizon, and use a stochastic model to prove the approximation of the deterministic model is reasonable.

A similar approach is used by Leeftink et al. [22]. They design a blueprint schedule for a multi disciplinary clinic with open access, where all appointment schedules are jointly optimized. To do so, they first solve a deterministic model, after which stochasticity is introduced using the Sample Average Approximation method to make the solution more robust.

From Figure 8 and literature we found, we see that little research has been done on the percentage of patient types within a blueprint, using a stochastic model to deal with demand uncertainty. And the research that has been done does not fit the problems that occurred within Isala. Therefore, we combine the methods found in literature to provide a blueprint scheduling method, optimal for the problem at the Internal medicine department of Isala.

3.3.2 Blueprint KPIs

Several KPIs are commonly used in literature for designing blueprints. The most important KPIs are access time, waiting time, utilization, and overtime. An overview of these KPIs with their description is given in Table 3 [23].

Table 3: Blueprint KPIs

KPI	Description
Access time	The time during which a patient is waiting for his/her appointment at home. [23]
Waiting time	The time during which a patient is waiting for his/her appointment at the day of appointment in the hospital [23]
Idle time	The occupancy of the resources (mostly caregivers)[24]
Overtime	The time caregivers have to work outside regular hours[24]

3.4 Conclusion

In this chapter, we want to find relevant literature to answer the following research question:

What information does the literature provide about optimal outpatient clinic blueprint scheduling?

To answer this question, we first positioned this paper in the framework of [9], after that, we identified the different types of blueprints, and then used the snowballing technique to find more in depth information about optimal blueprint scheduling that fits this research most. Finally, we identified the most important KPIs optimize the blueprint on. From this literature review, we conclude that we are going to use a stochastic optimization model to find the optimal blueprint for the nephrology department of Isala, optimizing both the amount of overtime and idle time.

4. Modelling technique

In this chapter, the stochastic model to find the optimal blueprint we created will be explained. This will be done to answer the following research question:

How can we model the planning of dynamic care paths within the outpatient clinic?

The answer to this question will lead to a blueprint schedule for the internists of the internal medicine department of Isala. First, the assumptions made will be described. Second, the mathematical model is formulated. Third, the solution approach is discussed, after which we will explain how to formulate a blueprint from the model output. Finally, the conclusion of this chapter is given.

4.1 Model description

In this section, the model created is described in detail. The goal of this model is to create the optimal blueprint, containing the number of appointments of each patient type per week, by balancing the overtime and idle time. With the blueprint, the needed time for all patient types per week can be determined.

The model is a 2-stage stochastic program. The difference between these two will be explained later in this chapter. For now, we will describe the stochastic model since this model is an extension of the deterministic model.

The decision variables of the program are divided into a first- and second-stage variables. The first stage variable has no scenario as an index, so this variable should be determined independently from the scenarios. The second stage variables depend on the scenario, which means that the values of these variables differ between scenarios. With this type of modeling, it is possible to deal with uncertainty in certain parameters. In this model, the demand per week for each type of patient follows a distribution and is not constant, while the determined blueprint is similar for each week.

The outcome of the model is a blueprint for one week that can be repeatedly used by internists and planners to deal with an uncertain demand of types of patients. The model is described in detail in the following sections.

4.1.1 Model assumptions

In this section, the assumptions needed for the model are described. To make the model as realistic as possible, the assumptions made are kept to a minimum, but it is not feasible to model the whole reality in this model. The assumptions made for the model are:

- The model uses historical appointment data based on empirical distributions of the demand per patient type per period.
- The demand per week is generated from appointment data. It is assumed that the week the appointment took place is also the demanded week for an appointment. This assumption can be biased by the historical capacity of the outpatient clinic.
- The model only creates a division for control appointments, not for new patient appointments. The time spent on new patient appointments is subtracted from the capacity an internist has.
- It is assumed that not all appointments in the 'yellow zone' take place. It is assumed that a certain percentage of the appointments that have criteria in the 'yellow zone' also actually take place since an internist takes a look in the patient file of that patient and determines

whether a patient needs an appointment or not. This number is based on discussions with nephrologists and the change a patient needs an appointment or not.

- It is assumed that if a patient needs an appointment, this appointment takes 15 minutes. In this case, it does not matter whether this appointment takes place physically or by phone.
- It is assumed that all patients in the 'other' group need an appointment of 15 minutes. Since this group has not been analysed and therefore no decision on whether this group needs an appointment or not has been made.

4.2 Mathematical model

4.2.1 Sets

The set notation is used, where I are the patient types, R are the resources (internists) and S is the set of scenarios for which the model is run. The sets and their description can be seen in Table 4.

Table 4: Sets used in the MILP model

Set	Description
$\boldsymbol{i} \in \boldsymbol{I}$	Set of patient types
$\boldsymbol{r} \in \boldsymbol{R}$	Set of resources
$\boldsymbol{s} \in \boldsymbol{S}$	Set of scenarios

4.2.2 Parameters

Table 5 shows the parameters used in the MILP model. $Dmd_{i,r,s}$ is the weekly demand of a certain patient type and internist. Cap_r is the capacity per internist per week.

Table 5: Parameters used in the MILP model

Parameter	Description
$\boldsymbol{Dmd_{i,r,s}}$	Weekly demand of patient type i at internist r in scenario s
$\boldsymbol{Cap_r}$	Available time slots per week of internist r
$\boldsymbol{\alpha}$	Parameter to set the max percentage of overtime slots
Weightover	Weight assigned to the overtime part of the objective
Weightidle	Weight assigned to the idle time part of the objective.

4.1.3 Variables

Table 6 shows the variables used in the MILP model. The goal of the model is to balance the number of slots in idle time P_{irs} and extra slots O_{irs} needed to cover the patients in all scenarios.

Table 6: Variables used in the MILP model

Variable	Description
$\mathbf{X_{ir}}$	# slots opened for patient type i at internist r
$\mathbf{Y_{irs}}$	# slots of patient type i at resource r used in scenario s
$\mathbf{O_{irs}}$	# extra slots needed for patient type i at internist r in scenario s
$\mathbf{P_{irs}}$	# empty slots for patient type i at internist r in scenario s

Z_{irs}	Binary variable indicating whether extra slots are needed for patient type i in scenario s (1) or not (0)
B	Binary variable to determine whether alpha is met (0) or not (1).

4.1.4 Objective

The goal of the model is to minimize both the idle time of the internists and the extra slots needed to treat the patients. The second part of the objective gives a penalty if alpha is exceeded. Therefore, in the objective, the sum of both is minimized over all scenarios, resources, and patient types.

$$\min \sum_i \sum_r \sum_s (WeightIdle * P_{irs}) + \sum_i \sum_r \sum_s (Weightover * O_{irs}) + \beta * 10000 * (\frac{\mathbf{1}}{\boldsymbol{S} * \boldsymbol{I} * \boldsymbol{R}} * \sum_r \sum_s \sum_i Z_{rsi} - \alpha)$$

4.1.5 Constraints

Several constraints have been formulated to ensure the model is solved as preferred. The constraints will be explained one by one. Constraint (1) ensures that no more slots are used than are available in regular time. The number of slots opened for each patient type is the first stage decision in this model, and the number of slots used is the second stage. Constraints (2-3) make sure that in a certain percentage (α) of scenarios, enough slots are opened to treat patients in regular time. β is a binary variable that becomes 1 if α is not met, enabling to penalize the objective when this is the case. Constraint (4) makes sure the number of opened slots does not exceed the capacity of each internist. Constraint (5) calculates the idle time, and constraint (6) makes sure all demand is met. Finally, constraints (7) and (8) determine the value of Z, this is done through a bigM constraint, since Z is either 1 if the number of overtime slots is larger than 0, or 0 if the number of overtime slots is 0.

Table 7: Constraints

Constraint	Description
$Y_{irs} \leq X_{ir} \ \ \forall i, r, s$	(1) Do not use more regular slots than available in regular time
$\frac{1}{S * I} * \sum_r \sum_s \sum_i Z_{rsi} - \alpha < BigM * \beta$	(2) Check whether the number of scenarios in overtime is larger or bigger dan α.
$\alpha - \frac{1}{S * I} * \sum_r \sum_s \sum_i Z_{rsi} < BigM * (1 - \beta)$	(3) Check whether the number of scenarios in overtime is larger or bigger dan α.
$\sum_{i=1}^{I} X_{ir} \leq Cap_r \ \forall r$	(4) Capacity constraint
$P_{irs} = X_{ir} + O_{irs} - Dmd_{irs}, \forall i, r, s$	(5) Idle time constraint
$Y_{irs} + O_{irs} = Dmd_{irs} \ \forall i, r, s$	(6) Demand constraint
$O_{i,r,s} \leq BigM * Z_{irs} \ \forall i, r, s$	(7) Determine value of Z 1
$Z_{irs} \leq O_{irs} \ \forall i, r, s$	(8) Determine value of Z 2
$X_{ir} \in \mathbb{Z}^+ \ \ \forall i, r$ $Y_{irs} \in \mathbb{Z}^+ \ \ \forall i, r, s$ $O_{irs} \in \mathbb{Z}^+ \ \ \forall i, r, s$ $P_{irs} \in \mathbb{Z}^+ \ \ \forall i, r, s$ $Z_{irs} \in \{0, 1) \ \ \forall i, s$	(9) Side constraints

4.3 Solution approach

In this section, the solving method of the model is explained. We are going to use the same methodology as [22], so first, a deterministic solution to the problem is determined based on an average demand scenario, and after that, SAA is used to create a more robust solution to the problem that can be applied in practice. The deterministic problem is discussed in the first section, and the Sample Average Approximation is discussed in the second section.

4.3.1 Deterministic solution

To find a solution to the problem, we first solve a deterministic version of the model, in which we consider an average scenario only. The average is determined from the data from the data dashboard of Chapter 2, where the total number of patients who had an appointment at an internist in 2022 is divided by the number of weeks this internist worked in 2022.

Because we run the model only for one scenario, the Constraints (2) and (3) are removed from the model, and the objective is slightly adapted:

$$\min \sum_i \sum_r \sum_s (P_{irs} + O_{irs})$$

where s is a set of 1 scenario.

Now, the model finds the optimal division of overtime and idle time, given the average patient demand per week. This model will find a feasible solution to the problem. The quality of this solution is assessed by simulating 1000 demand scenarios and evaluating the performance of the system with the solution out of the deterministic version of the model.

4.3.2 Stochastic optimization

Since the patient demand fluctuates over the weeks, a deterministic solution probably does not give the most robust solution to use in practice. Therefore, we want to optimize the solution for multiple patient demand scenarios. Therefore, the model is solved as a two-stage stochastic model, considering multiple patient demand scenarios.

The stochastic model cannot be solved in reasonable time. Therefore, we use Sample Average Approximation (SAA). The SAA algorithm approximates the objective value by evaluating a sample of N scenarios. These scenarios are randomly drawn from the scenario population, in our case based on the patient demand distributions. M runs of N scenarios are performed, and the outcomes of the optimal run out of the M runs are chosen to test the performance for a very large (say 10000) number of scenarios. The optimal run is determined based on the average of the M runs, and the outcome that differs least from the average is chosen as optimal. In this way, the performance of the model can be tested, and performance in reality is simulated. For more information on SAA, please refer to [25]–[27].

Using the SAA algorithm also allows us to say something about parameters such as the allowed fraction of time in which overtime is needed, through monitoring the fraction of scenarios that incur overtime. This is a useful parameter since overtime has a large impact on the workload of the internists.

4.4 From model to blueprint

The optimal outcomes of the optimization are used to create a blueprint for the nephrologists of the internal medicine department of Isala. With the values of $X_{i,r}$ from the model, the number of slots to reserve for each patient type and internist can be determined. With these numbers, the schedule per week for an internist can be made. An example of a blueprint is given in Figure 9. In this Figure, we see that a number of slots are assigned to a nephrologist for each patient group. The total number of slots opened for each nephrologist is shown as a number on top of each

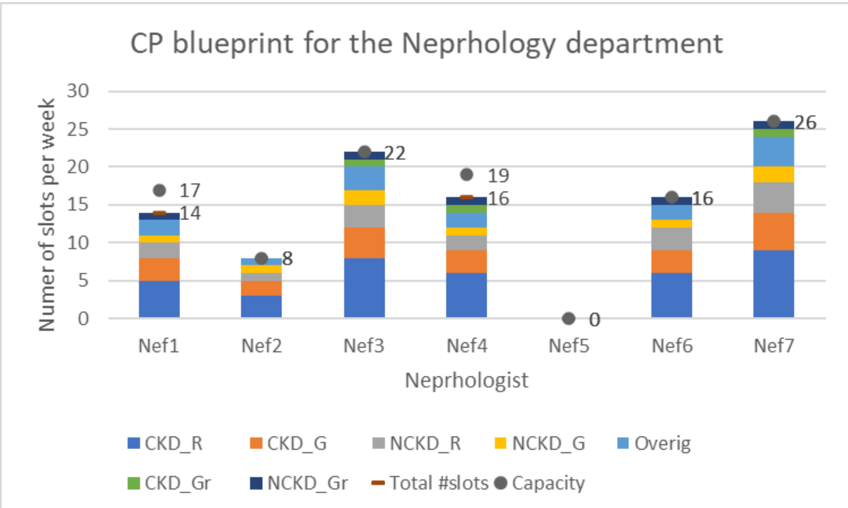


Figure 9: Example of a blueprint composed out of the outcomes of the model.

column. The grey dots shown for each nephrologist represent the capacity this nephrologist has to treat control patients. It is important to note we only talk about the number of control patients, so the number of new patients and short phone consultations are left out of the blueprints. These are also not calculated by the model, since these types of appointments are less relevant for the problem we are trying to solve in this research. Slots for control patients all take 15 minutes.

4.5 Conclusion

The research question to answer in this chapter is:

How can we model the planning of dynamic care paths within the outpatient clinic?

We answered this question by developing a stochastic mixed integer program, which has as the most important input the patient type demand, capacity of caregivers, and objective weights. The output of the model is an optimal blueprint in which the number of slots per patient type opened to treat patients is given.

5. Experiments and results

In this chapter, the research question about the implementation of the criteria-based appointment planning method is answered. The research question is as follows:

> *How can criteria-based appointment scheduling be implemented at the internal medicine outpatient clinic?*

This question is answered by setting up an experiment design, through which we see what the best way to implement the abovementioned method is.

5.1 Experimental design

5.1.1 Model input

In this section, the input values for the model are discussed. Each internist has a capacity, based on the number of hours in his or her contract, and for each patient type, a demand distribution is known for the number of patients per week needing an appointment. The demand distributions of each patient type are shown in Table 8. It should be noted that these distributions are truncated and only have values larger or equal to 0. In Appendix A, the distribution tests and goodness of fit statistics are shown, with an explanation. For all patient types, the normal distribution is chosen, except for the CKD-Yellow patient type, for this patient type, the lognormal fits best.

Table 8: Input parameter demand distribution

Patient type	**Distribution**	**Mean number of patients**	**Standard deviation**
CKD-Red	Normal	37.50	10.20
CKD-Yellow	Normal	19.60	6.20
NCKD-Red	Normal	14.80	4.58
NCKD-Yellow	Normal	8.29	3.90
Other	Normal	14.31	4.59

Besides the demand distribution among the patient types, also the capacity of an internist needs to be determined. This is done based on the capacity set at the beginning of each year for an internist. This is called the norm. The norm consists of the total number of outpatient clinic hours an internist should spend. To get a reliable number of hours an internist should spend on control patients, the focus group of this research, the number of hours per week an internist spends on other types of patients should be subtracted from the norm hours. The calculation of the number of CP appointments an internist can handle per week is shown in Table 9.

Table 9: Calculation of capacity per nephrologist.

Nephrologist	**Total capacity per week (hours)**	**Time spent on NP and TC per week (hours)**	**Time available for CP's (hours)**	**# CPs that can be planned (rounded)**
Nef1	10.0	3.9	6.1	24
Nef2	4.0	0.2	3.8	15
Nef3	9.9	1.3	8.6	34
Nef4	7.9	1	6.9	28
Nef5	13.0	0.0	13	52
Nef6	11.1	1.4	9.7	39
Nef7	13.8	1.2	12.6	50

The next parameter to determine is the allowed percentage of scenarios for which overtime is allowed. After discussions with different stakeholders within the internal medicine department of Isala, it is chosen to use an allowed percentage of allowed overtime of 10%, resulting in a value for α of 0.1. Later in this chapter, an experiment on the value of α is discussed.

5.1.2 Model parameter settings

For the SAA algorithm, we solve the model for N runs and M scenarios. These numbers have of large influence on the experimental design and reliability of the proposed solution.

The value of M is determined based on a reasonable solving time of the model, since the researcher, and also Isala in the future need to run the model within a reasonable time frame. On the other hand, the model does not need to be run daily, so the runtime does not need to be very short. Also, the outcomes of the model need to be reliable. For the experiments, the number of scenarios (M) is set to 1000. The model is solved with CPLEX 20.1, for 1000 scenarios, the runtime of the model is approximately 25 minutes.

The model uses appointment data based on a distribution generated out of appointment data for 2022. We assume that data from 2022 is representative, since this year lies not too far in the past, and there are no factors such as COVID-19 that had a major impact on the appointments that year. Moreover, the weekly patient arrivals for the whole department follow a distribution based on the data of 2022. These arrivals are divided among the internists based on the working hours each internist has in a week. This is done to have enough data available to generate a reliable patient arrival probability.

The number of runs is determined based on the so-called 'replication/deletion approach', described in [28]. This method determines the required number of runs based on the width of the confidence interval compared to the mean. The calculations for the number of runs can be found in Appendix B: Number of runs. The minimal number of runs required according to the 'replication/deletion' approach is 3. After the replication/deletion approach, we also want to look at the number of runs based on the number of runs after which no 'new' blueprints are generated. This is done by running the model 25 times, and after the model does not find a new blueprint, the number of runs is determined. The number of runs after which no 'new' blueprint was found is 6. So, for the experiments in this thesis, we use 6 runs.

This means, that after 6 runs with 1000 scenarios, the variables with an optimal outcome are chosen and tested for a very large number of scenarios.

5.1.3 Experiments

Various experiments are executed. We first analyse and compare the deterministic and stochastic solutions on performance. To compare the deterministic and stochastic solutions, we determine the value of the stochastic solution (VSS) and the Expected Value of Perfect Information (EVPI) [29]. We further divide the experiments into theoretical experiments and practical experiments. To further analyse the model, theoretical experiments are performed to see what the effects of certain constraints and model parameter settings are. Practical experiments are experiments executed to see what happens if certain input parameters change. We describe the experiments we investigate below, indicating whether it is a theoretical or practical experiment:

- **Theoretical: VSS and EVPI**
  As discussed, the deterministic and stochastic solutions are compared. To do so, the VSS is determined[29]. To analyse the solution of the stochastic model, the EVPI is determined. The VSS is an indicator of what the optimality gap is between the deterministic variant of the model and the stochastic model. The EVPI can be used to see the value of perfect

information. Mathematically, this means that the decisions made in the first stage can be adapted to already account for the realization in the second stage.

- **Theoretical: effect of value of α**
  After discussions with several stakeholders in Isala, it is determined that the model strives at a maximum of 10% of the scenarios in which overtime occurs (α). In this experiment, we want to investigate what the effect is of the value of α, by running the model with multiple values of α. The value of α is experimented from 0.1 to 0.9 with steps of 0.1. The solutions and decision variables will be compared.
- **Practical: Difference current situation**
  We developed a method to implement criteria-based appointment scheduling, and we want to see what the effect of this method is on the current situation. Therefore we compare the outcomes of the current situation and the criteria-based outcome.
- **Practical: Overtime and idle time weights**
  The main part of the model is to balance the overtime and idle time. It is important to see the effect of weighting both parts of the balance, and what the effect of applying different weights is. Seven experiments were performed. One with equal balance and three with unequal balances on both sides.
- **Practical: increased patient demand**
  Based on [30], it is likely that the number of patients coming to the internal medicine departments in the Netherlands will grow by 10.6% in 2029, compared to 2019, and 14.1% in 2034. Therefore, it is reasonable to test how much capacity is needed in the blueprints of the internists, and whether it is doable to handle all patients with the same capacity.

All in all, we performed two experiments for the VSS and EVPI, eight experiments on α, an experiment on the current situation, seven on the weights of overtime and idle time, and five on the increased patient demand which makes in total 23 experiments. With these experiments, we test the performance of the model, from both a theoretical and a practical perspective.

5.2 Results

In this section, we will discuss the results of the experiments. For each experiment, the results are given per subsection and the reasoning behind the outcomes of the experiment is given. The experiments are executed as described in the previous section, Section 5.1.2. For each experiment, we compare the results based on certain KPIs. These KPIs are:

- The number of scenarios in which there is overtime and idle time, expressed in a percentage.
- The maximum slots overtime and idle time per nephrologist and scenario, summed over the patient types
- The average size of overtime and idle time if these are larger than zero.
- The standard deviation of the overtime and idle time if these are larger than zero.
- The objective value of the solution.

In various experiments, we compare the results of an experiment with a base case. This base case is composed based on the most realistic combination of input parameters. The most realistic combination is composed based on discussions with the stakeholders in Isala. The input parameters for the base case scenario are as follows:

- The percentage of yellow patients having an appointment is 85%
- The weight for the overtime is 2
- The weight for the idle time is 1
- The alpha is 0.3
- The demand is distributed as described in Table 8

The base case input parameters are the same for each experiment unless stated in the introduction of the experiment.

5.2.1 VSS and EVPI

To calculate the VSS, the model is run for an average demand scenario. The outcomes of this run are put in the model where we fix the blueprint (so the X_{ir}) and run the model for 10,000 scenarios to test its performance.

The outcomes are compared to a base case model, to compare the value of the stochastic solution. When calculating the VSS, this is:

$$VSS = Obj_{base\ case} - Obj_{avg\ scen} = 331261 - 351349 = -20088$$

So, the true objective is approximately 20.000 lower when applying the stochastic solution. Percentage wise, the objective is around 6% lower. The number suggests that there are 20000 less overtime and/or idletime slots in the 10000 scenarios. This indicates that the VSS is not really high, but this view can be misleading if we look at the other KPI values. Therefore, we compare the KPI values of the average scenario and the stochastic solution in Table 10.

Experiment	Number of slots	Overtime	Idletime	Max Overtime	Average Overtime	StDev Overtime	Max Idletime	Average Idletime	StDev Idletime	Objective
Average Scenario	89	24.8%	21.6%	14	2.72	1.76	13	2.26	1.76	351349
Base case	94	21.0%	26.8%	15	2.26	1.65	9	2.51	1.44	331261
	-6%	**15%**	**-24%**	**-7%**	**17%**	**6%**	**31%**	**-11%**	**18%**	**6%**

Table 10: VSS results compared with the base case.

We see that the number of slots for the average is 6% lower than the base case. This logically leads to an increase in scenarios with overtime and a decrease in scenarios with idle time, since there are less slots available to cover a scenario with a large demand, and the chance of idle time at a low-demand scenario is decreased. The average size of overtime is 17% higher for the average scenario than for the stochastic model. However, the idle time size is lower for the average scenario. In Figure 10 and Figure 11, the blueprints for respectively the average scenario and the base case are shown. If we compare these figures, we see that less space is used for nephrologist 2, 3 and 7 in the average scenario blueprint. None of these nephrologists is at its capacity, so we could say that the model is not optimal for these nephrologists, since these nephrologists do have a lot of overtime. We therefore say that the average scenario does not lead to an preferred solution.

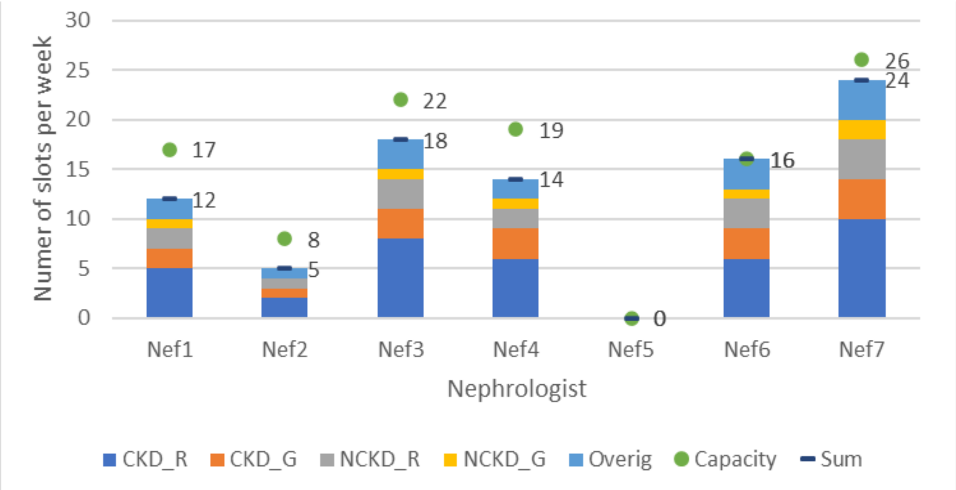


Figure 10: Blueprint for the average scenario

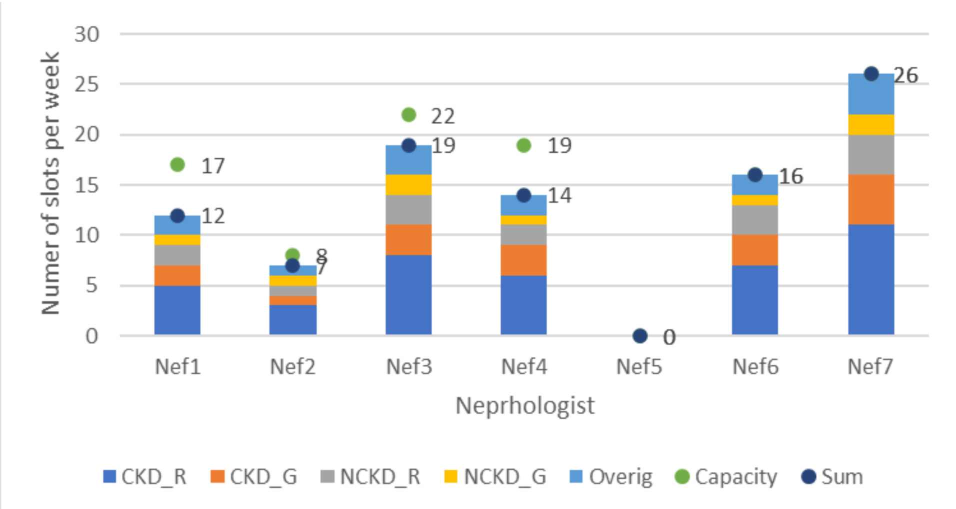


Figure 11: Base case blueprint

For the EVPI, we allow $X_{i,r}$ to change over the scenarios, so the variable will be $X_{r,s,i}$. This makes sure to adapt the blueprint based on the scenario, so in this case, it is assumed to have perfect information. In practice, this will never happen, but it can serve as a lower bound for our model. In principle, the objective will equal 0. Only if the demand exceeds capacity, there will be overtime. When running the model, the objective equals 63650. Comparing this objective with the base case objective, the EVPI is:

$$EVPI = 63650 - 331261 = -267611$$

This means, that when having perfect information and when Isala can change the blueprint for each demand scenario, the objective value will be 267.611 lower. The interpretation of this value is that the number of overtime slots and number of idle time slots is 0, unless there is more demand than capacity.

5.2.2 Theoretical Alpha

In this experiment, we test the impact of the value of α. The value of α is tested from 0.1 to 0.9, with steps of 0.1. This means we perform eight experiments on this value. For each α,, the model is run six times, after which the optimal input value for the 10000 scenarios is chosen. These input values are chosen based on the average of the six runs performed. The input values closest to the average are selected.

We first look at the results of the 10000 runs. The results are shown in Table 11, displaying the KPI values of the experiments. Interesting to see is that when α is larger than 0.3, there is no change in KPI values anymore.

Table 11: Results of the experiments on alpha

Experiment	Number of slots	Overtime	Idletime	Max Overtime	Average Overtime	StDev Overtime	Max Idletime	Average Idletime	StDev Idletime	Objective
Alpha 0.1	95	19.5%	29.0%	15	2.30	1.69	15	2.76	1.88	334385
Alpha 0.2	95	20.1%	28.7%	15	2.28	1.65	12	2.42	1.89	331778
Alpha 0.3	**94**	**21.0%**	**26.8%**	**15**	**2.26**	**1.62**	**14**	**2.51**	**1.69**	**331261**
Alpha 0.4	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261
Alpha 0.5	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261
Alpha 0.6	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261
Alpha 0.7	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261
Alpha 0.8	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261
Alpha 0.9	94	21.0%	26.8%	15	2.26	1.62	14	2.51	1.69	331261

The fact that the KPI values for an α larger than 0.3 do not differ anymore is caused by α being met for these values. This means that the percentage of scenarios in which overtime occurs is lower than the value of α, and so the outcomes of the model do not differ based on a value of α anymore. For values of α 0.1 and 0.2, we see that the objective increased compared to α =0.3. This is caused by α not being met, and therefore the objective value is penalized based on how much α is exceeded. This is also the reason why the objective is higher for $\alpha = 0.1$ than $\alpha = 0.2$. Furthermore, the other KPI differences for α values 0.1 to 0.3 do not differ significantly. This is probably because the blueprints for the different α-values only differ one slot, and therefore also do not differ significantly in performance. The blueprints for the α-values can be found in Appendix C: Blueprints experiments on α

5.2.3 Difference current situation

This experiment is about testing the benefits of applying the new way of appointment planning regarding the time needed for control patients at the nephrology department. To compare the appointment planning strategy based on medical criteria with the current appointment planning strategy, we need to run the model with a configuration that approaches the current situation as good as possible. This is done by putting the percentage of yellow patients needing an appointment to 100% and adding the CKD_Green and NCKD_Green groups to the input data, representing the patients with and without CKD not needing an appointment.

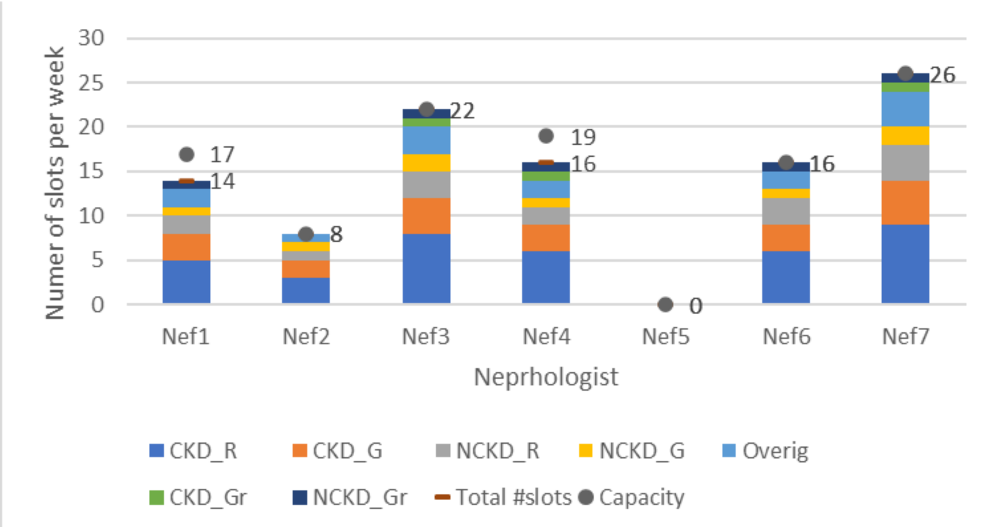


Figure 12: Blueprint for the current situation

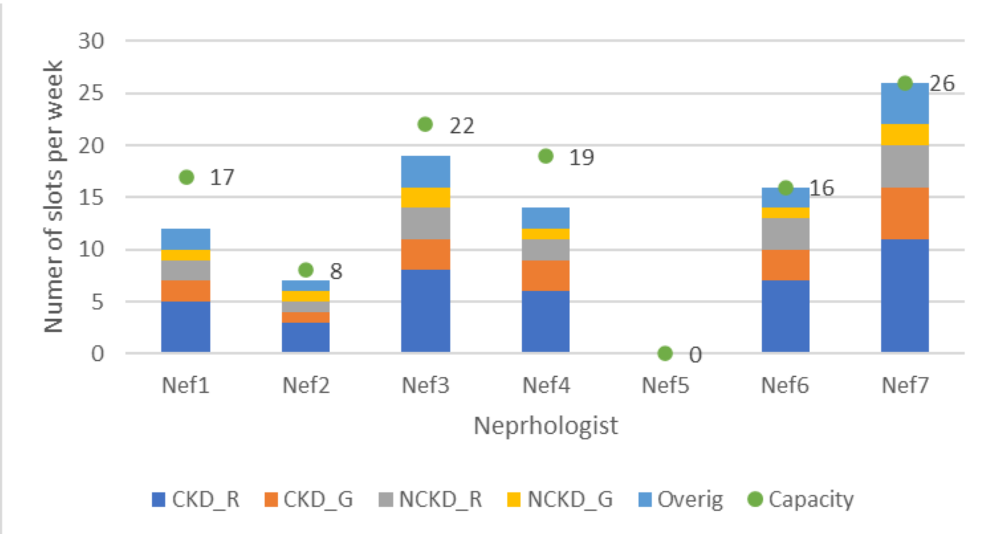


Figure 13: Blueprint for the base case

The blueprint of the current situation is shown in Figure 12. In this Figure, we see that almost all nephrologists are at capacity. When comparing the blueprint of the current situation with the blueprint of the base case in Figure 13 , we see that there is significantly more capacity available in the base case blueprint.

To further investigate the differences between the base case and the current situation, we take a look at the differences in KPI values, shown in Table 12.

Table 12: KPI values base case and current situation

Experiment	Number of slots	Overtime	Idletime	Max Overtime	Average Overtime	StDev Overtime	Max Idletime	Average Idletime	StDev Idletime	Objective
Current situatic	102	28%	34.9%	18	2.98	2.41	14	2.91	1.87	438493
Base case	94	21.0%	26.8%	15	2.26	1.65	9	2.51	1.44	331261
Difference	**8%**	**25%**	**23%**	**17%**	**24%**	**32%**	**36%**	**14%**	**23%**	**24%**

In Table 12, we see that the number of slots for the current situation is 8% higher than for the base case. Interesting to see is that all other KPIs have increased much more. The percentage of scenarios in which is overtime and idle time is around 25% higher, and also the average and standard deviations of the amount of overtime and idle time are around 25% higher. These increases are probably caused by two extra demand groups being added to the data and therefore the standard deviation of the demand also increased.

This also explains the difference in increase for the number of slots and the other KPIs. If we take a look at the sum of the means of the patient group demands without the CKD_Gr and NCKD_Gr groups, this number equals 94.5, as can be concluded from Table 8. The sum of the patient demand means with CKD_Gr and NCKD_Gr equals 101.5. This is also an increase of approximately 8%. This declares an increase of 8% in number of slots used. However, the other KPI values are much higher than 8%. This is caused by the increased standard deviation caused by adding an extra patient group.

Based on the blueprints shown in Figure 12 and Figure 13 and the KPI values, introducing criteria-based appointment planning for control patients at the nephrology department will have a 8% decrease in the time needed to treat these patients, and a 17% decrease in the chance of overtime.

5.2.4 Weights objective

In this experiment, the weights for the objective are varied, to see what the effects of these weights are on the KPIs and blueprint. Seven experiments are performed, with different combinations of weights for the objective overtime and idle time. The combinations of the weights are given in Table 13.

Table 13: Weight experiments

Exp No.	Overtime	Idle time
1	1	1
2	1	2
3	1	3
4	2	1
5	2	3
6	3	1
7	3	2

A higher weight for overtime or idle time means that in the objective, this part weights heavier on the value of the objective function, and thus the model tries to reduce this part of the objective more than when the weights are equal or opposite.

The outcomes of these experiments differ significantly. First, we take a look at the blueprints that are the output of the six runs of 1000 scenarios. We compare the blueprint for which both weights are set to 1 in Figure 15 and the blueprint for which the weight for overtime is 1 and for idle time is 2 in Figure 14.

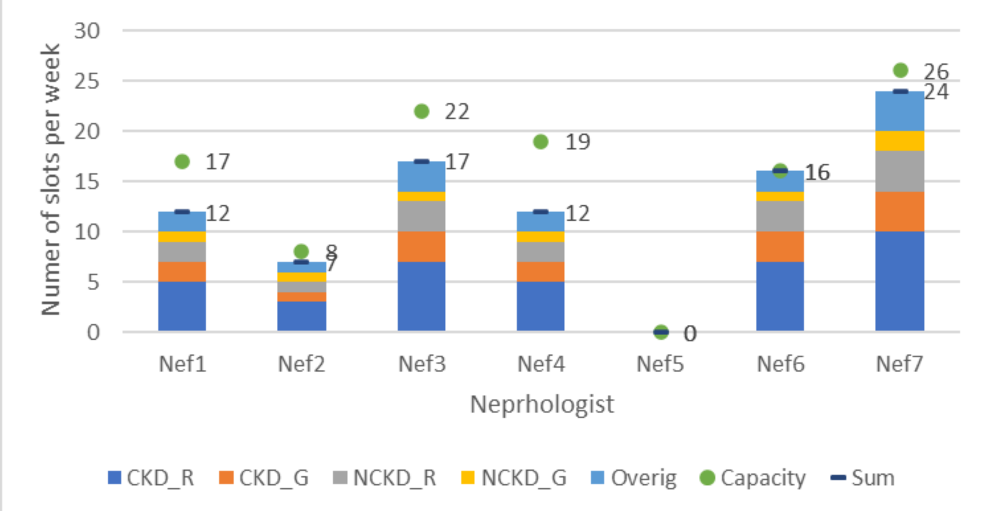


Figure 14: Blueprint for weight 1-2

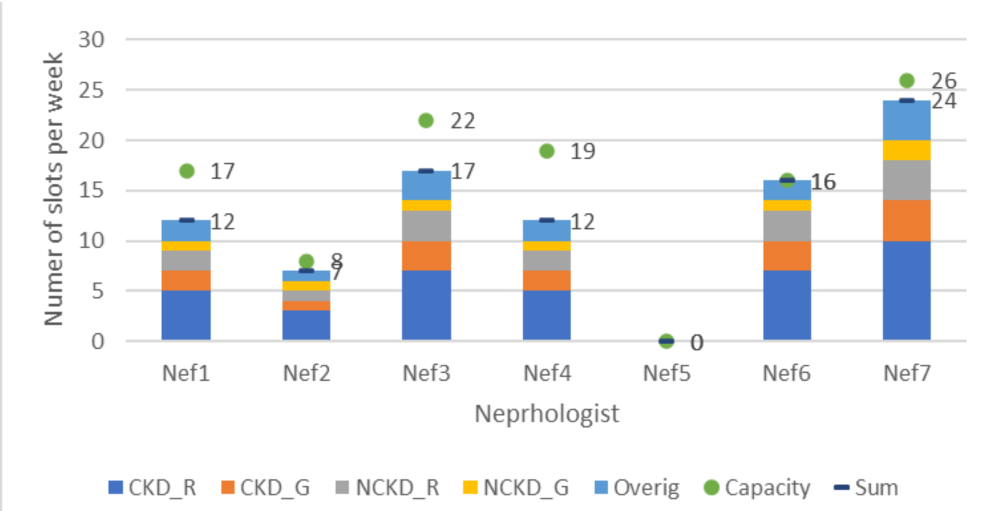


Figure 15: Blueprint for weight 1-1.

In the Figures, we see that the blueprints change depending on the weights given in the experiments. If we focus on reducing the idle time by putting extra weight on it in the objective the blueprint contain less slots to treat patients. This indeed reduces the chance of idle time, but on the other hand, increases the chance of overtime, as can be seen in Table 14.

In Figure 17 and Figure 16, we compare the situation with equal weights (Figure 17) and putting more weight on the overtime (Figure 16). What we see is that in the situation where we put more weight on the overtime, more slots are opened to treat patients. This is as expected since opening more slots leads to a decrease in the chance of having overtime. On the other hand, this leads to an increase in idle time scenarios.

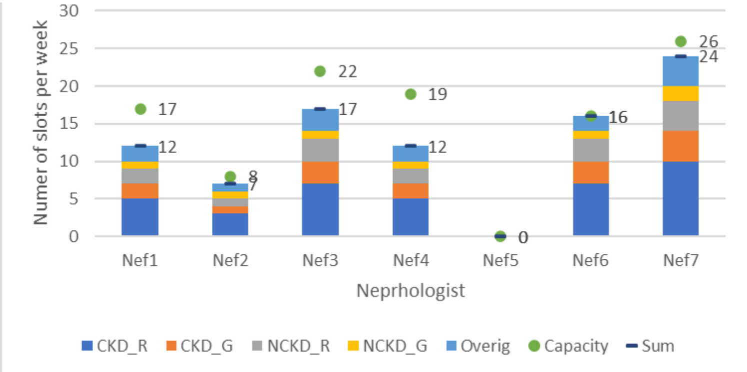


Figure 17: Blueprint for weight 1-1

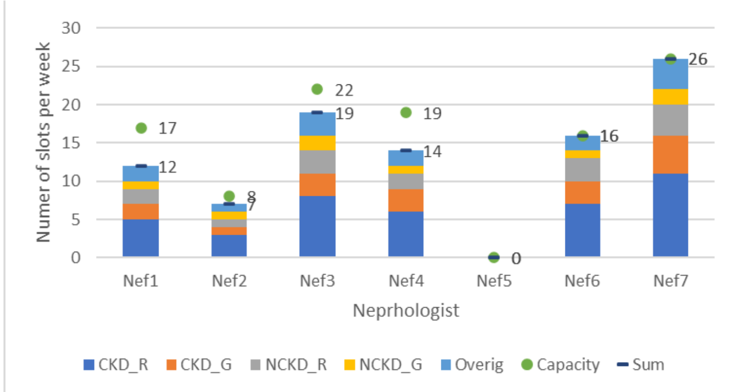


Figure 16: Blueprint for weight 2-1

In Table 14, the KPI results of all weight experiments can be seen. For this experiment, the objective values are less relevant since we multiply the value of the overtime and idle time with a certain weight and therefore the objective will change significantly based on this weight.

When looking at the number of slots in the experiments, these follow a logical progression through each weight experiment. If we focus more on reducing idle time by adding weight to this component of the objective, the number of slots decrease and when we add weight to the overtime component of the objective, the number of slots increase.

Increasing or decreasing the number of slots, respectively leads to a decrease and increase in scenarios in which overtime occurs, and the opposite counts for the idle time. When looking at the average overtime and idle time, their progression is the same as for the percentage of overtime and idle time. When the percentage overtime decreases, the average overtime size also decreases and opposite. The same counts for the average idle time. The standard deviation of the overtime size does not showing the typical pattern as described above.

Table 14: KPI values for the weight experiments

Experiment	Number of slots	% Overtime	% Idletime	Max Overtime	Average Overtime	StDev Overtime	Max Idletime	Average Idletime	StDev Idletime	Objective
Weight 1-1	88	25.3%	21.4%	15	2.46	1.65	14	2.16	1.44	346219
Weight 1-2	79	34.3%	14.2%	15	2.68	1.64	13	1.77	1.19	414619
Weight 1-3	69	44.3%	8.5%	13	3.49	1.92	11	1.48	0.97	531618
Weight 2-1	94	21.0%	26.8%	15	2.26	1.65	9	2.51	1.44	331261
Weight 2-3	81	32.1%	15.7%	15	2.68	1.64	14	1.88	1.29	395997
Weight 3-1	100	16.7%	35.3%	13	2.31	1.80	11	3.15	1.81	339460
Weight 3-2	92	22.4%	24.6%	15	2.31	1.62	13	2.28	1.81	332021

5.2.5 Increased demand

In this experiment, we want to test what the effect of an increase in demand is on the blueprint and the over- and idle time. To do so, we change the configuration of the base case where we increase the mean of the patient group demands with a certain percentage. The standard deviation is not changed, since it is hard to see what the effect is on the standard deviation when the patient demand increases. This standard deviation will likely decrease if there is more demand, but we do not know an exact number, so therefore it is chosen to keep the standard deviation the same as it is right now.

We tested a 10%, 20%, 30%, and 40% increase in demand compared to the base case. The KPI results are compared and put in Table 15. We will go through the results per experiment.

Table 15: Results increased demand experiment.

Experiment	Number of slots	% Overtime	% Idletime	Max Overtime	Average Overtime	StDev Overtime	Max Idletime	Average Idletime	StDev Idletime	Objective
+10% Demand	101	22.8%	27.8%	16	2.75	2.16	13	2.71	1.69	481929
+20% Demand	103	28.9%	22.1%	18	3.35	2.67	12	2.39	1.57	417994
+30% Demand	108	32.0%	21.8%	21	4.38	3.36	10	2.44	1.46	484063
+40% Demand	108	39.1%	15.7%	24	5.11	3.97	9	1.99	1.17	571749
Base case	94	21.0%	26.8%	15	2.26	1.64	9	2.51	1.19	331261

If we look at the 10% extra demand, the total number of slots needed to treat the control patients increases from 94 to 101. The number of scenarios with overtime and idle time stay almost equal compared to the base case. Also, the average size of overtime and idle time stay quite the same if we compare to the base case. The standard deviation of the overtime and idle time increases, this is caused by the increased variability of the demand scenarios since the mean increased but the standard deviation stayed the same.

When looking at the 20% increase in demand, we see that the system starts to struggle with the amount of patients. The amount of slots opened is 103 and especially the amount of scenarios with idle time increases, from 21.0% to almost 29%. Besides that, the average size of overtime also increases to 3.35 slots. Following the increased average, also the standard deviation has increased, from 1.64 to 2.64. The average idle time decreased, indicating that the blueprints are more filled with patients than for the base case scenario.

At a 30% demand increase, we see that the number of slots opened (108) is equal to the total capacity of the nephrology department. The percentage of overtime scenarios increased to 32%, and also the average and standard deviation increased, compared to the 20% demand increase, and even more for the base case. Opening the maximum amount of slots indicates that the system is on its boundaries and that an increase in capacity is needed to treat all patients coming to the nephrology department of Isala.

A 40% increase in demand further confirms that more capacity is needed to treat these amounts of patients. Overtime occurs in almost 40% of the scenarios, and also the size of the overtime increases significantly. The idle time decreased more than 10% compared to the base case, suggesting that the blueprints are completely filled in 85% of the scenarios.

Conclusionary, we see that the system can handle an increase in demand of 10% and 20%. This meets the demographic growth indicating that in the coming year, more than 10% extra capacity is needed at an internal medicine department [30]. Introducing the criteria-based appointment scheduling strategy makes it possible to handle the increase in demand stated in the abovementioned report.

6. Conclusion and discussion

In this chapter, the conclusion of the research is discussed. In Section 6.1, we answer the research questions stated in Chapter 1, Section 6.2 provides a discussion of the research.

6.1 Conclusion

This research aimed to find a method for implementing criteria-based appointment scheduling in the Internal Medicine department of Isala. To find an answer to this, we divided the research into multiple steps that combined form the answer to the aim of the research.

To understand what the actual problem of the Internal Medicine department is should we first understand what the current situation within the Internal Medicine department looks like. We took one specialty of the Internal Medicine, the Nephrology to represent the Internal Medicine department. Patients coming to the nephrologists are often chronic patients, having an appointment with a nephrologist each period, for example, three months. A consequence of this is that patients often visit a nephrologist without a specific reason, only because he or she should visit the nephrologist according to the system. This is what should be changed.

A data analysis has been performed to find the answer to the question of what the potential of preventing unnecessary visits to a nephrologist is. In other words, we wanted to know how many patients visited a nephrologist without medical reason. Only 57% of the appointments had a direct medical reason for a nephrologist visit. 19% of the appointment had no medical reason to visit, and for 25%, the decision whether an appointment is needed should be made after a patient file review by the nephrologist. So, we conclude that developing a method that prevents unnecessary appointments at a nephrologist has a big capacity improvement potential.

In literature, we searched for the best way to develop an optimal blueprint, when implementing the method to prevent unnecessary visits to a nephrologist. The outcome of the literature study is that we can create a Mixed Integer Linear Program that outputs a blueprint. This blueprint contains the number of slots opened for each resource, in this case, a nephrologist.

Based on the outcome of the literature review, we formulated a Mixed Integer Linear Program (MILP) that outputs an optimal blueprint. Input for the model is the patient type demand and capacity of the nephrologists. With this model, we can see what the effect of implementing criteria-based appointment scheduling is on the time needed to treat all patients. Besides that, the model also gives the opportunity to see what the effect of changing several input parameters is.

To see what the effect of criteria-based appointment scheduling is on the blueprint, several experiments have been performed. The outcomes of the experiments are that the new appointment strategy gives the opportunity to reduce the blueprint by 15% while maintaining the chance of overtime, or reducing the chance of overtime by 25% while remaining the same number of slots available.

Finally, we combine the findings in all steps in the process to formulate an answer to the main research aim, to find a method to implement criteria-based appointment scheduling at the Internal Medicine department of Isala. We conclude that by introducing criteria based on which can be determined whether an appointment is needed or not, 19% of the appointments can be reduced based on medical criteria, and for 25% of the appointments can be determined after a patient file lookup whether an appointment is needed or not. This results in a decrease of overtime of 31% when keeping the same blueprint as it is right now, and can result in a decrease in the amount of time needed of 8%, while maintaining the same chance of overtime.

6.2 Discussion

In this section, the assumptions and limitations of the research are discussed. During the research, we had to make certain choices that had to be made. These choices had an impact on the process of this research and the outcomes of it. The choices and their impact are discussed.

6.2.1 Discussion on results

In this section, we will discuss the choices made during this research project and what the impact of these choices is on the results.

When defining the patient groups we worked with during the research, we divided the patients into three groups, patients with Chronic Kidney Disease, patients with other nephrology-related diseases, and an other group. The 'other' group is left out of the analysis, since it was not in the scope of this research to do an in-depth analysis on what type of patients were in this group, and whether it was possible to apply the developed method to this group too. This could have influenced the patient division, and therefore the results of this research.

In Chapter 2, we wanted to know how many patients had an appointment while there was no reason to have an appointment from a medical perspective. This was done by comparing the medical data of all appointments with criteria, and based on that can be determined whether an appointment is needed or not. We wanted to take the most recent data available for this, but not all medical parameter is checked before each appointment. Therefore, we took a maximum of one year before the appointment date as valid data to base the decision on. This could have an impact on the results of the dashboard. It could be that a data point is used more than once. If for example a patient has an appointment every three months, and the blood pressure value is only measured once a year, this blood pressure data is used for all four appointments the patient had in that year. This means that if the blood pressure indicated that an appointment was needed for the time it was measured, in the data dashboard, it gave four times an indication for an appointment. And the other way around, if the blood pressure did not indicate appointment the time it was measured, it did not indicate all four appointments the patient had that year.

The data dashboard contains data of all appointments that took place at the nephrology department in 2022. This means that there is one year of data available to analyse on. When we determined the distribution of the weekly demand per patient type, we used the data of the dashboard to determine the mean and standard deviation of the weekly number of patients per patient type that arrived at the nephrology department of Isala. If we take the weekly number of patients of one year, this means that we have 52 data points to determine our distributions on. The distributions found have a relatively high standard deviation compared to the mean. If we had used more data points to determine the distribution on, we would probably have a more accurate distribution with lower standard deviations.

In the model and experiments of Chapters 4 and 5, we used the demand distributions based on 52 weeks of data. When we determined the capacity of the nephrologist, the holiday weeks of the nephrologists were subtracted from the total number of weeks in a year. In the capacity calculations, it is assumed that a nephrologist works 44 weeks in a year, while in the demand calculations, the demand of all 52 weeks is used to determine the weekly demand. Therefore, the actual demand per week per nephrologist is higher than the demand used in the model. This means that the capacity constraint is a bit too loose compared to reality. This could also be the reason why in the experiment described in Section 5.2.3 about the current situation, the blueprint is not filled completely, while in reality, the nephrologists all run into overtime all the time.

6.2.2 Contributions

Our literature study is mainly focused on how to create a blueprint and what methods are available to create the optimal blueprint. The outcomes of this literature study are that a Stochastic Program is a well-fitting way of developing an optimal blueprint. After we indeed created a blueprint and did our experiments on this, it has indeed been a good choice to formulate an SP to develop the optimal blueprint for the nephrology department. Talking about impact on science, we say that this research showed that increasing the variability of appointments by adding an extra step in the appointment scheduling process ís leading to an increase in performance of the system. Despite the statistics arguing against it.

When we talk about the impact on practice of this research, the potential of the developed method for reducing the time needed to treat chronic patients at an outpatient clinic is very high. There is a large need in healthcare for methods to treat more patients while using the same or less amount of resources. The method we developed in this research causes a decrease of at least20% in appointments needed to treat the same patient group.

6.2.3 Managerial implications

This section discusses the managerial implications of this research. The outcomes of this research are reason for discussion, since they are not all in line with the way healthcare is organized right now.

The experiment results discussed in Chapter 5 show a relatively high percentage of idle time scenarios. Isala has as goal to have a maximum of 15% idle time, while the numbers shown in Table 11-14 show an idle time percentage of around 30%. This could imply that the proposed method leads to a too high percentage of idle time. However, the researchers argue against this.

As Kuiper et al. [16] discuss, idle time does not necessary increase when a schedule is more loose, giving more space for variability in demand. Medical professionals will have enough other jobs to do to use eventual idle time, resulting in a more flexible and even spreaded work load for a medical specialist.

The experiment on the objective weights, described in Section 5.2.4 Weights objectivealso gives reason for discussion for the people in Isala. On the one hand, they can focus on reducing idle time, to meet the maximum 15% of idle time, but on the other hand, and that is also the recommendation in this research, they can focus on reducing the overtime, since the focus on this results in more flexible schedules and possibilities to deal with patient demand fluctuations.

6.2.3 Further research

This research is conducted as a case study at the nephrology sub-department of the Internal Medicine department of Isala. The goal of this assignment was to develop a method to implement criteria-based appointment scheduling at the Internal Medicine department of Isala. By developing this method for the nephrology department, it is not said that this method can also be used for the whole Internal medicine department of Isala. Each sub-department has its own specialty and also its own type of patient. The developed method works well for chronic patients coming every period, but probably not for patients that visit the outpatient clinic once because of the comparison between results of different outpatient visits. Therefore, further research has to be done on whether it is possible to extend the method developed for the nephrology department to other parts of the Internal Medicine department of Isala.

The research conducted was about implementing a method to implement criteria-based appointment scheduling. We created a method to determine based on medical reasons whether an appointment is needed or not. Besides the medical reasons, the patient can also have a reason why he or she wants to have an appointment. Isala wants to implement the patient side of determining whether an appointment is needed by sending the patient a questionnaire based on which can the need for an appointment be determined. It is recommended to do further research on the patient perspective of criteria-based appointment scheduling, to see what the impact of such a questionnaire is on the time needed to treat this patient group, and what the patients think of implementing this.

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A: probability distribution patient demand

In this Appendix, the goodness of fit test statistics are shown for each patient group. To determine the input data for the model, we used the appointment data from 2022, as shown in the dashboard. Per patient group, the appointments in this group are extracted from the Power BI dashboard. It is determined in which week the appointment took place and, in this way, the weekly demand in 2022 can be determined.

For each patient type, the weekly demand data is used for an R script to determine the distribution that fits best for the data. The fit of each distribution is determined based on five goodness of fit statistics.

CKD Red

The CKD Red patient type has lowest goodness of fit values for the Weibull and Normal distribution. In Figure 18 and Table 16, an overview of the distributions is given. For this figure, and the figures of all other patient groups, a selection is made for the normal, lognormal, and Weibull distribution, since the shape of the data and the shape of the distributions are most equal for these distributions.

In this case, it is chosen to use a normal distribution, since the goodness of fit statistics is (almost) lowest for all tests, and this is the most easy-to-use distribution.

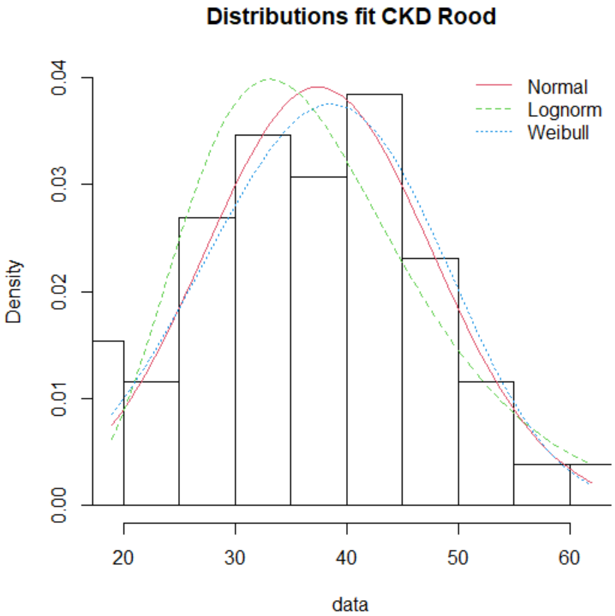


Figure 18: CKD Red distributions plotted over the data.

Table 16: goodness of fit statistics for the CKD Red patient type

Distribution	Normal	Exponential	Poisson	Lognormal	Gamma	Weibull
Kolmogorov-Smirnov	0,086	0,387	0,170	0,113	0,106	0,085
Cramer-Von Mises	0,057	2,198	0,222	0,102	0,070	0,049
Anderson-Darling	0,408	10,922	1,752	0,699	0,498	0,354
AIC	310,126	382,723	311,595	310,709	309,078	309,165
BIC	314,029	384,674	313,546	314,611	312,981	313,068

CKD Yellow

For the CKD Yellow patient type, the test statistics for the lognormal distributions are the lowest, as can be seen in Table 17. So, we use this distribution, with a meanlog of 2,933 and sdlog of 0,306.

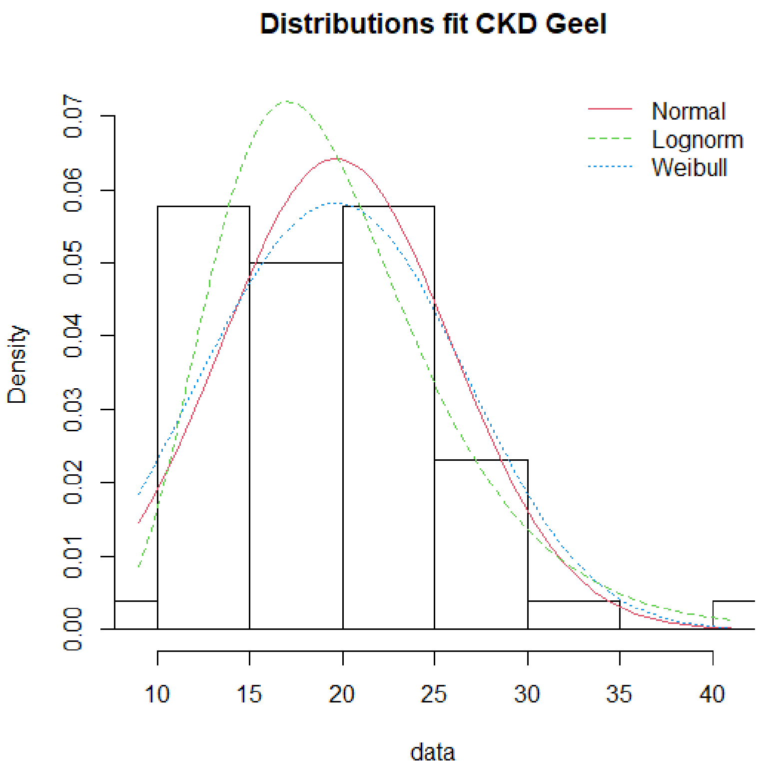


Figure 19: CKD Yellow distributions plotted over the data.

Table 17: the goodness of fit test for the CKD Yellow patient type

Distribution	Normal	Exponentia l	Poisson	**Lognormal**	Gamma	Weibull
Kolmogorov - Smirnov	0.130220 8	0.4084445	0.163611	**0.1020364 1**	0.1135120 3	0.110740
Cramer-Von Mises	0.133739 1	2.4162303	0.315761 2	**0.0745560 8**	0.0836177 2	0.121275 1
Anderson-Darling	0.794136 8	11.762883 0	2.536728 0	**0.4170183 6**	0.4627038 3	0.806704 1
AIC	341.5769	416.0452	348.4659	**334.6848**	335.4805	342.1815
BIC	345.4794	417.9965	350.4171	**338.5873**	339.3830	346.0840

NCKD Rood

For the NCKD Red Patient type, the test statistics are lowest for the Weibull distribution, as can be seen in Table 18. In this case, it is chosen to use a normal distribution, since the goodness of fit statistics is (almost) lowest for all tests, and this is the most easy-to-use distribution.

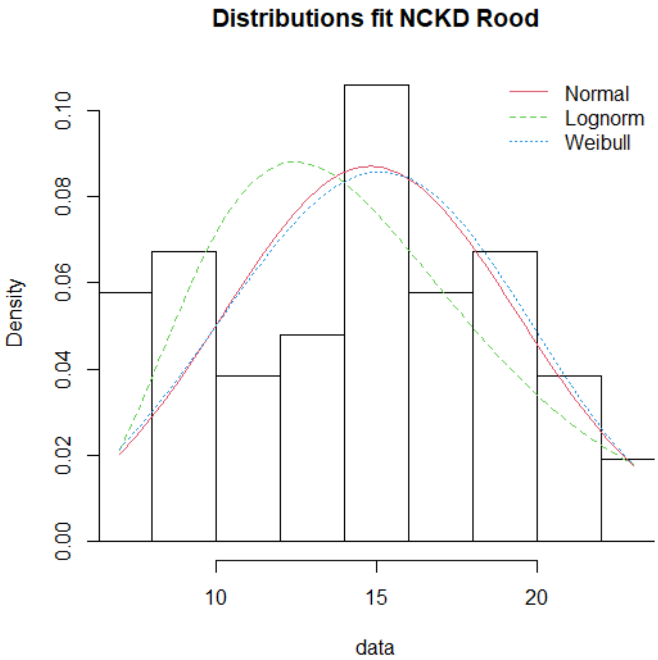


Figure 20: NCKD Red distributions plotted over the data.

Table 18: the goodness of fit test for the NCKD Red patient type

Distribution	Normal	Exponential	Poisson	Lognormal	Gamma	**Weibull**
Kolmogorov-Smirnov	0.1029311	0.376700	0.1647037	0.1548647	0.1359993	0.1024556
Cramer-Von Mises	0.0719115	2.235812	0.3383002	0.1938284	0.1391696	0.0641906
Anderson-Darling	0.5278277	11.138972	2.2988360	1.1887229	0.8806617	0.4890584
AIC	309.8884	386.2953	312.6619	314.7988	311.8479	308.3317
BIC	313.7909	388.2465	314.6132	318.7013	315.7504	312.2341

NCKD Yellow

The normal distribution has the lowest values for the NCKD Yellow patient type, as can be seen in Table 19. Therefore, we choose this distribution for this group. The mean is 8,29 and the standard deviation is 3,90.

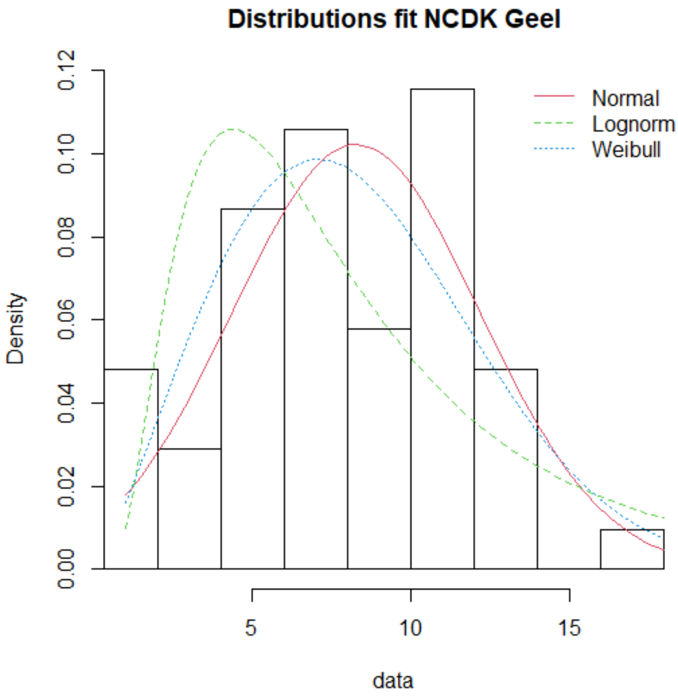


Figure 21: NCKD Yellow distributions plotted over the data.

Table 19: the goodness of fit test for the NCKD Yellow patient type

Distribution	**Normal**	Exponential	Poisson	Lognormal	Gamma	Weibull
Kolmogorov-Smirnov	**0.10246856**	0.299122	0.2122905	0.1753598	0.1479163	0.110298
Cramer-Von Mises	**0.08125755**	1.174017	0.4987141	0.3937547	0.2271188	0.119613
Anderson-Darling	**0.53669543**	6.011192	4.1993619	2.5102829	1.4816525	0.894704
AIC	**293.2263**	325.9459	308.6885	313.5500	300.8728	293.8164
BIC	**297.1288**	327.8971	310.6397	317.4525	304.7753	297.7189

Other

For the Other patient type, it is chosen to use the normal distribution, since this distribution has the almost lowest values of the parameters.

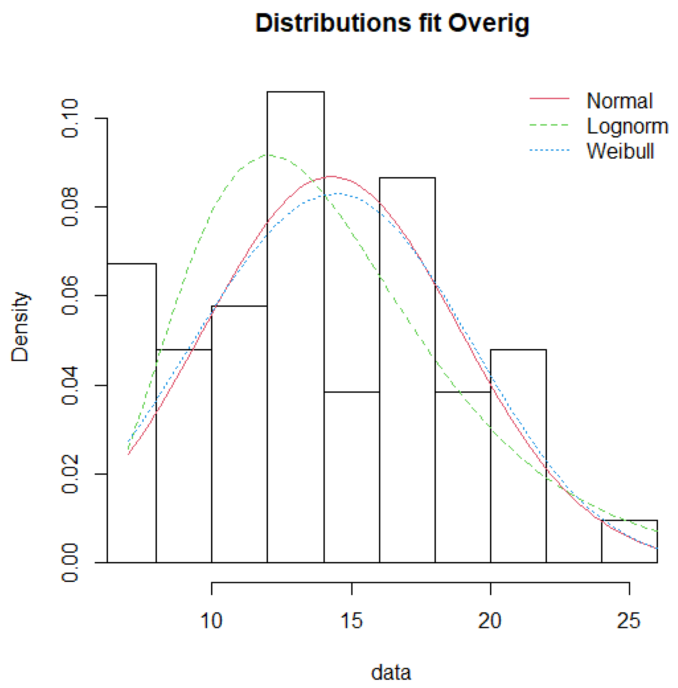


Figure 22: Other distributions plotted over the data.

Table 20: the goodness of fit test for the Other patient type

Distribution	Normal	Exponentia l	Poisson	Lognorma l	Gamma	Weibull
Kolmogorov - Smirnov	0.0864968 3	0.3869123	0.169944 0	0.113202 0	0.106455 2	0.0847586
Cramer-Von Mises	0.0568120 1	2.1979864	0.221926 7	0.101729 0	0.069958 1	0.0487146 3
Anderson-Darling	0.4075545 4	10.922441 4	1.752273 2	0.698901 6	0.497935 6	0.3543060 3
AIC	310.1260	382.7229	311.5947	310.7085	309.0783	309.1653
BIC	314.0285	384.6742	313.5460	314.6110	312.9808	313.0678

B: Number of runs

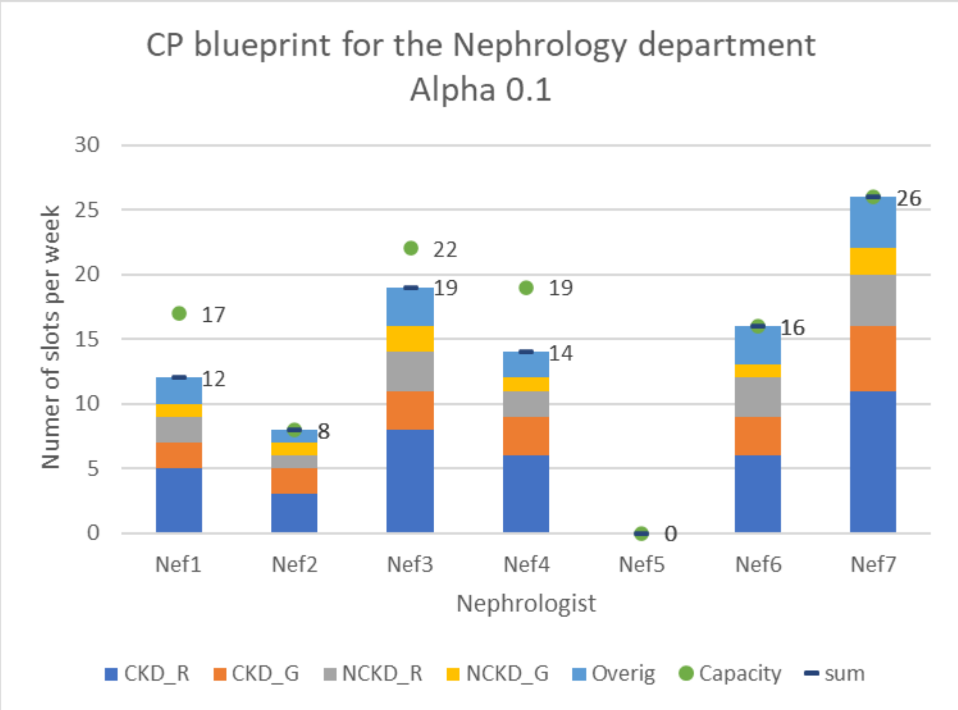
This appendix shows the replication/deletion approach described in [28]. The approach is executed in Excel, where the stochastic model is solved for 1000 scenarios 10 times. A KPI is chosen to base the number of runs on. The chosen KPI is the total number of slots opened to treat the control patients. This KPI is put in an Excel file and the required parameters are determined. In Figure 23 one can see that the number of runs for which the test statistic is first YES is at the third run. This means that the number of runs we need is three.

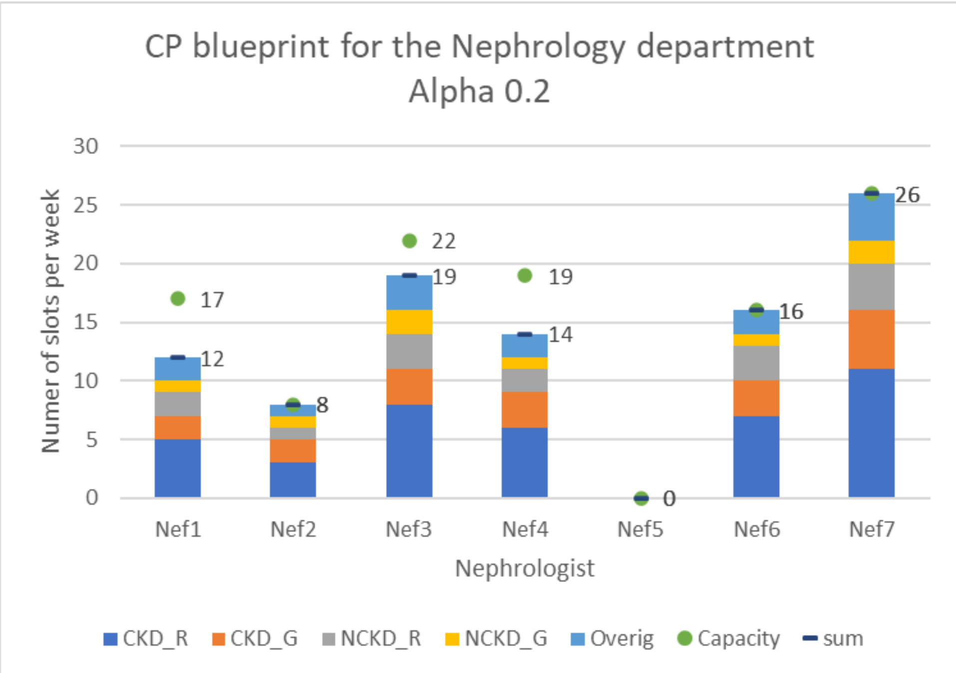
	A	B	C	D	E	F	G	H
1	n	KPI (*)	Mean	Var	Tvalue	CIHW (**)	Error	Test
2	1	84						
3	2	83.00	83.5	0.5	12.7062	6.353102	0.076085	NO
4	3	84.00	83.66667	0.333333	4.302653	1.434218	0.017142	YES
5	4	84.00	83.75	0.25	3.182446	0.795612	0.0095	YES
6	5	84.00	83.8	0.2	2.776445	0.555289	0.006626	YES
7	6	84.00	83.83333	0.166667	2.570582	0.42843	0.005111	YES
8	7	83.00	83.71429	0.238095	2.446912	0.451279	0.005391	YES
9	8	84.00	83.75	0.214286	2.364624	0.387002	0.004621	YES
10	9	83.00	83.66667	0.25	2.306004	0.384334	0.004594	YES
11	10	85.00	83.8	0.4	2.262157	0.452431	0.005399	YES

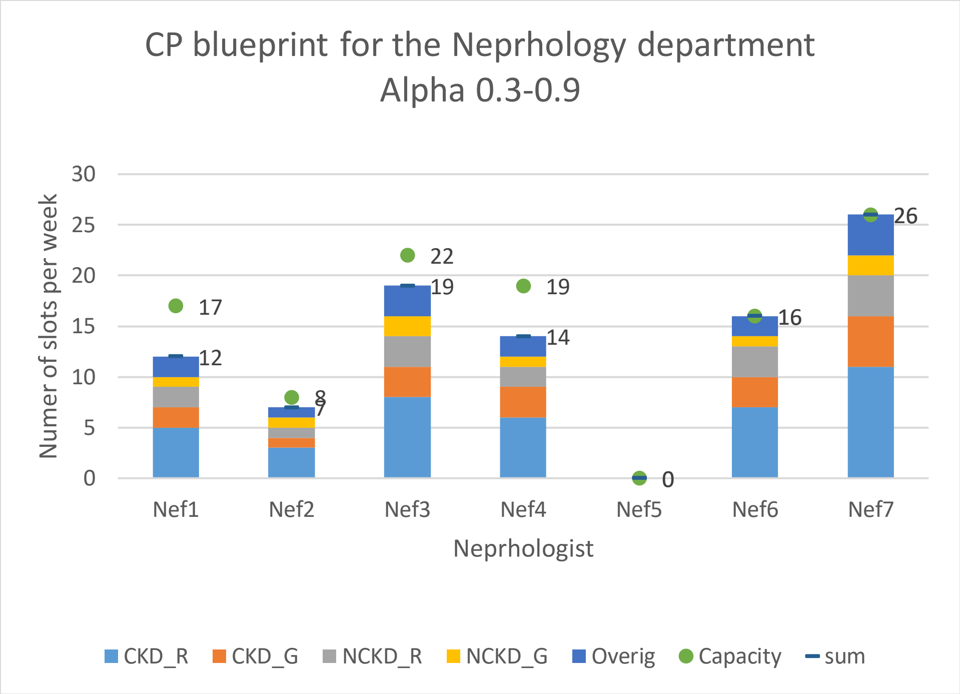
Figure 23: Excel file to determine the number of runs.

C: Blueprints experiments on α

In this appendix, the blueprints for the different values of α are shown.







CP blueprint for the Neprhology department
Alpha 0.3-0.9
Numer of slots per week
30
25
20
15
10
5
0
17
12
8
7
22
19
19
14
0
16
26
Nef1
Nef2
Nef3
Nef4
Nef5
Nef6
Nef7
Neprhologist
CKD_R
CKD_G
NCKD_R
NCKD_G
Overig
Capacity
sum