Improving Efficiency in Allocating Pediatric Ambulatory Care Clinics

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Abstract

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Low utilized resources is a common problem in the health care sector. As health care costs and the need for more efficient operations increases, managers are looking for new methods to increase the utilization of their resources. At Seattle Children's Hospital in Seattle, managers of the outpatient pediatric ambulatory care clinic are experiencing low utilization of their clinic rooms, while not being able to meet the demand for rooms from the specialty clinics. In this thesis I present a new optimization model for allocating generally equipped clinic rooms to specialty clinics. The new optimization model increases the utilization of clinic rooms; using fewer rooms than before to meet the demand. A discrete-event simulation is used to investigate the impact of randomness and to evaluate and compare the performance and behavior of the current allocation method and the proposed allocation method. The optimization and simulation model were tested on data provided by the outpatient ambulatory care clinic at Seattle Children's Hospital. In the test case, the number of required rooms to meet the provider's schedule was significantly reduced.

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DEDICATION

To my wife and our two boys

Chapter 1

INTRODUCTION

With the introduction of the Affordable Care Act, an addition of 30 million to 34 million Americans are estimated to receive health care insurance (Anderson, 2014). With the increase in demand for health care service, managers of hospitals and other health care facilities are looking for new methods to help increase the resource utilization. Lower operation costs are demanded at the same, forcing the management to take imminent actions against the lowest utilized recourses.

Seattle Children's Hospital outpatient pediatric ambulatory care clinic at the hospital's main campus at Sandpoint Way in Seattle schedules 27 outpatient specialty clinics every week and each specialty clinic has multiple providers and each provider attends three to twelve patients per time slot. The outpatient pediatric ambulatory care clinic has a total of 104 rooms that are spread across three floors and are divided into four types of rooms to accommodate the needs of those specialty clinics: examination rooms; procedure rooms; consult rooms; and team rooms. Of the 27 specialty clinics, nine specialty clinics either need specially equipped rooms or are running at a steady capacity for every single week and have dedicated rooms of the outpatient pediatric ambulatory care clinic reserved. The rest of the 18 specialty clinics do not require a repeated number of rooms for every time slot and therefore are able to share the 55 generally equipped rooms. In order to keep track of the distribution of rooms between the specialty clinics the typical work week is divided into morning and afternoon time slots, creating ten, four hour time slots per week.

With time sampling and general observation, the pediatric ambulatory care managers of the outpatient pediatric ambulatory care clinic have noticed a general low room utilization, where rooms are used for less than 50% of the time that the clinic is open. At the same time the specialty clinics are asking for extra rooms to accommodate their current flow of patients. Each specialty clinic has a specialty clinic manager who is responsible for the room availability for the clinic. The management of the outpatient pediatric ambulatory care clinic and the specialty clinic managers are interested in developing a new method of allocating the rooms in order to improve the efficient use of the rooms.

Increasing the number of rooms without increasing the flow of patients through the system will only decrease the utilization of the rooms. In order to increase the efficient use of the existing rooms a new methodology has to be introduced to the management of the outpatient pediatric ambulatory care clinic. This thesis presents a new optimization model that minimizes the number of rooms used to meet the demand, increasing the utilization of the rooms.

With the high number of possible combinations of room allocation the scale of the system has grown in size, so it is difficult to handle manually. In this thesis, I develop an optimization model in order to get the best possible outcome for the system. Scheduling patterns for the patient encounters, called templates that are individually created by each provider, are input to a deterministic optimization model. Even though the starting time and duration of the encounters are scheduled in the templates, the system has variability when it comes to arrival times and duration. To be able to address such variability, a discrete-event simulation model is built to compare the current performance of the method to that of the new proposed method.

Furthermore, I developed an optimization method that further improves room allocation by optimizing the starting time of the patient encounters for every template, creating a synergy between the templates to optimize the room utilization for the demanded patient encounters.

Chapter 2

LITERATURE REVIEW ON HEALTH CARE AND SCHEDULING PROBLEMS

2.1 Evolution of Outpatient Pediatric Ambulatory Care Clinics

In the 1960s medical providers and managers began to see the potential of providing quality patient care by expanding service to outpatient pediatric ambulatory care clinics. Vorzimer and Katz (1970) describe in their paper how specialized clinics at The Beth Israel Medical Center of New York City increased both patient and provider satisfaction as well as increase the quality of the provided service. Sherman and Slack (1971), who also were involved with The Beth Israel Medical Center of New York City, discussed the potential that outpatient ambulatory care services to reduce the number of patient encounters, save patient's and provider's time, and decrease the physician's workload by having health care workers with lower level of medical training do simple tasks, such as taking vital signs (height, weight, blood pressure, etc.), recording medical history, and collecting samples for laboratory testing.

Management's focus on the ambulatory care clinic shifted, the following two decades, from being dependent to the inpatient clinics into being an independent clinic (Dunn, 1999). A new approach was taken toward the ambulatory care clinics such as free-standing facilities designed to minimize distance traveled by staff and patients, and staff were cross-trained so they could serve more than one type of clinic. In the beginning of the 1990s ambulatory care clinic managers began experiments to improve the clinic's quality and cost control by introducing an efficient systematic process (Anderson, 1991). A year later (Anderson, 1992) pointed out that managers had started to realize that outpatient ambulatory clinics would undergo more growth than other traditional hospital clinics and that in order to meet that growth there had to be a clear message sent from managers that they were willing to invest in organization and administration of the ambulatory care clinics.

Allen and Weber (1995) urged the importance of strategic planning when running an efficient and cost effective outpatient ambulatory care clinic that provides quality service to its patients. Among planning issues identified by Allen and Weber are competition, physician employment, facility limitations, and system strategies. The first two planning issues, competition and physician employment, have to be constantly monitored and any changes that arise must be responded to quickly. While the latter two planning issues, facility limitations and system strategies, have metrics that stay fairly constant and upcoming changes usually have some amount of lead time. Furthermore they are constantly being improved over time by re-accessing strategies that improve performance and service quality.

2.2 Scheduling Problems in the Health Care Sector

There are three main scheduling factors on which to focus when scheduling an ambulatory care clinic: patient appointments; work shifts for physicians and staff; and facility availability.

A vast amount of work has been done in order to discover the ideal scheduling policy for outpatient clinics. Klassen and Rohleder (1996) created different appointment scheduling rules to minimize both patient waiting time and provider's idle time. The scheduling policy that balanced both of the objectives, scheduled patients that were expected to have low variance in their appointment length at the beginning of the time-slot leaving the patients that were expected to have high variance in appointment length to periods later in the time-slot.

Based partially on the work of Klassen and Rohleder, Cayirli et al. (2006) created a new approach to scheduling policies introducing a doctor/patient ratio factor that described the value of each party in time. THeir approach gives a more comprehensive set of solutions of scheduling policies than Klassen and Rohleder, and each policy is based on preference of performance chosen by each clinic.

Harper and Gamlin (2003) experimented with nine different types of scheduling policies with the goal of reducing patient waiting time once a patient has arrived at the clinic. Harper and Gamlin collected data at an ear, nose and throat clinic at a major hospital near London in the UK. They wanted to find an alternative to a prior policy that focused on increasing efficiency of the doctors time since it was considered more valuable than the patient's time, but they assumed by experiment that such policy gives the worst result in terms of patient waiting time. The schedule that showed the most reduction in patient waiting time at the clinic was based on zero delay in the starting time of the clinic's time-slot and a scheduling algorithm that schedules similar patients, in type and time, as far away as possible from each other within the time-slot, giving patients who are expected to have long visiting time priority in the algorithm.

Most prior work that has been done regarding scheduling problems for outpatient pediatric ambulatory care clinic are in terms of a single clinic that distributes rooms to its providers and less has been done where a set of clinics dynamically share a set of rooms over a certain time period.

Many of the optimization problems have been developed for operations room planning. Kuo et al. (2003) used linear programming techniques to allocate operation rooms to surgeons, based upon their historic financial activity and revenue generation. The model incorporates time spent on preparing and cleaning up the room, on operation, and patient to recovery and dressing after operation. Financial metrics were calculated from each surgeon's requirement for resource by giving the time for each resource a value. The model optimized weekly revenue of the clinic. Schmid and Doerner (2013) on the other hand used optimization to allocate operation rooms to hospitalized patients in order to minimize the in-patients stay at the hospital.

Allocation of clinic rooms was approached by Heim et al. (2001), where they created a linear optimization model that could be used as a tool to allocate clinic rooms to 16 specialty clinics at the University of Washington Medical Center. As a university medical center each providers' schedule changes every three months since they also carry a faculty position and therefore have different teaching schedule for each of the university's quarter term. Before the optimization model, the scheduling required one management staff-member 40 hours to create the schedule, but, with the introduction of the new optimization tool the time was reduced to less than 30 minutes. By collecting information from the providers such as minimum number of rooms needed, number of rooms preferred and preference of time availability, they were able to optimize the satisfaction of every provider by allocating the minimum number of rooms required at their most desired time. The excess rooms were allocated to those clinics who requested additional rooms and had the best measured performance factor of those clinics, so the model also increased the overall performance in general.

2.3 Resource Pooling

When having multiple low utilized resources and variability in demand, pooling and redistributing the resources can increase their utilization and therefore be more efficient. Pooling such resources can often be complicated since they often contain features that serve a specialized purpose, these features can be equipment in a clinic room or a knowledge of a worker. Punnakitikashem et al. (2013) created a comprehensive stochastic program that pooled excess nurse staffing and redistributed them to clinics that were understaffed. Information of workload between different units often would be available until at the beginning of each shift. Instead of either having the nurses working at an overstaffed unit or being sent home, the program would help the management to decide where to reallocate them, based on their knowledge and capability, to other units. Resource pooling and a reallocation method can be implemented with other types of resources and systems, such as outpatient clinic rooms at Seattle Children's Hospital, where we have low utilized rooms that are currently only used by a single clinic for every time slot. The biggest difference between the nurse scheduling and the room allocation is that the resources are at a fixed location in the outpatient pediatric ambulatory care clinic but can be moved in the nurse scheduling. A different type of industry, that has done similar work with fixed place resources, is the aviation industry when allocating boarding gates at airports.

Boarding gates that accommodate different airlines and aircrafts resemble clinic rooms that accommodate different patients and providers. Airlines usually want to have their aircrafts parked close to each other and their passengers to board them at a similar location, in order to reduce distance traveled by staff that provide customer and ground services to the planes and its passengers. In some cases at large airports airlines buy access to certain gates based on their location for their use. Whether airplanes from the same airline are spread evenly throughout the terminal or grouped together at adjacent gates, they are a good example of how low utilized resources can be distributed between different users. Genc et al. (2012) created a stochastic optimization model to increase the efficient use of airport gates at the Istanbul Atatrk Airport. Airlines would prefer to use gates for loading and unloading passenger but demand is higher than the supply of gates. With a limited number of gates the airport management wanted to increase the efficient utilization of the gates and to increase the revenue from airport service. An alternative to the airport gates is the apron, the tarmac parking and use of bus services to transport the passengers. By using a binary decision variables for airplanes and arrival times for gate assignment, the model allocated the airplanes to the gates using a new heuristic approach. Before, planes were allocated to gates based on their departure and the heuristic minimized the planes that needed to park at the apron. The new heuristic assigns planes based on their duration at the gate (difference in arrival and departure time) and therefore maximizes the time that the gates are in use, increasing the revenue from the airport gate service. Genc et al. (2012) ran several simulation models comparing the old heuristic to the new one and running the new heuristic for different non-linear algorithms. The new heuristic improved the financial characteristics of the system and by using a Single Leap Big Bang-Big Crunch algorithm the best financial performance was gained.

Kontoyiannakis et al. (2009) created a simulation model that tested three different gate allocation policies under severe delay conditions. Their simulation model showed that the most efficient use of the airport gates is to swap gates such that airplanes that are not having any efficient use of the gate, such as waiting for a delay, should be replaced with airplanes that are on time and can start serving passengers immediately.

A solution to a similar problem for outpatient pediatric ambulatory care clinics as introduced in this thesis could not be found in any prior literature. A good path can however be found of the evolution of the outpatient pediatric ambulatory care clinic and the problems that have been solved in the past. Ideas can be used from scheduling problems that the health care sector has already solved, a common dispute is however how metrics of performance should be evaluated and how to place a value on the provider's and patient's time, since increased competition has forced managers of health care facilities to now consider the value of patient time. Pooling resources is an idea that has proven to increase the utilization of resources that can be shared by different users. However, such pooling will contain a massive number of possible outcomes, that cannot be calculated manually and must use the aid of computer modeling.

Chapter 3

OPTIMIZATION AND SIMULATION METHODOLOGY

3.1 Current Process

The process of current room allocation to specialty clinics requires a collaboration among the outpatient pediatric ambulatory care clinic managers, specialty clinic managers, and providers. The process flow is described in Figure 3.1. The process has two main steps. The first step takes place at the beginning of every month, three months ahead of the specialty clinic date. A master plan determines which rooms are allocated to which specialty clinic and is presented as a layout of the rooms where each room has the specialty clinic ID and identification color. An example of the master plan can be seen in Figure 3.2, and a list of sample specialty clinic ID's in Table 3.1. Different master plans exist for every one of the ten time slots. The plan then repeats every week of the month and the same plan is used for every month. Changes to the master plan are made but they are rare and usually minor. Using the information about number of rooms for each clinic from the master plan and the number of patient encounters from the templates, the specialty clinic managers are able to create a working schedule for the providers. A daily plan is created for all ten time slots occurring each week, throughout the month and is based on the master plan. Each room is allocated to only one specialty clinic for each time slot and no other specialty clinic is scheduled to use that room during the time slot.

The second step begins when the daily plan is released and ends on the date when the patient encounter takes place, otherwise known as clinic date. The specialty clinic managers can either release a room that has been allocated to their specialty clinic and is not needed, or ask to get more rooms than initially allocated. The daily plan,

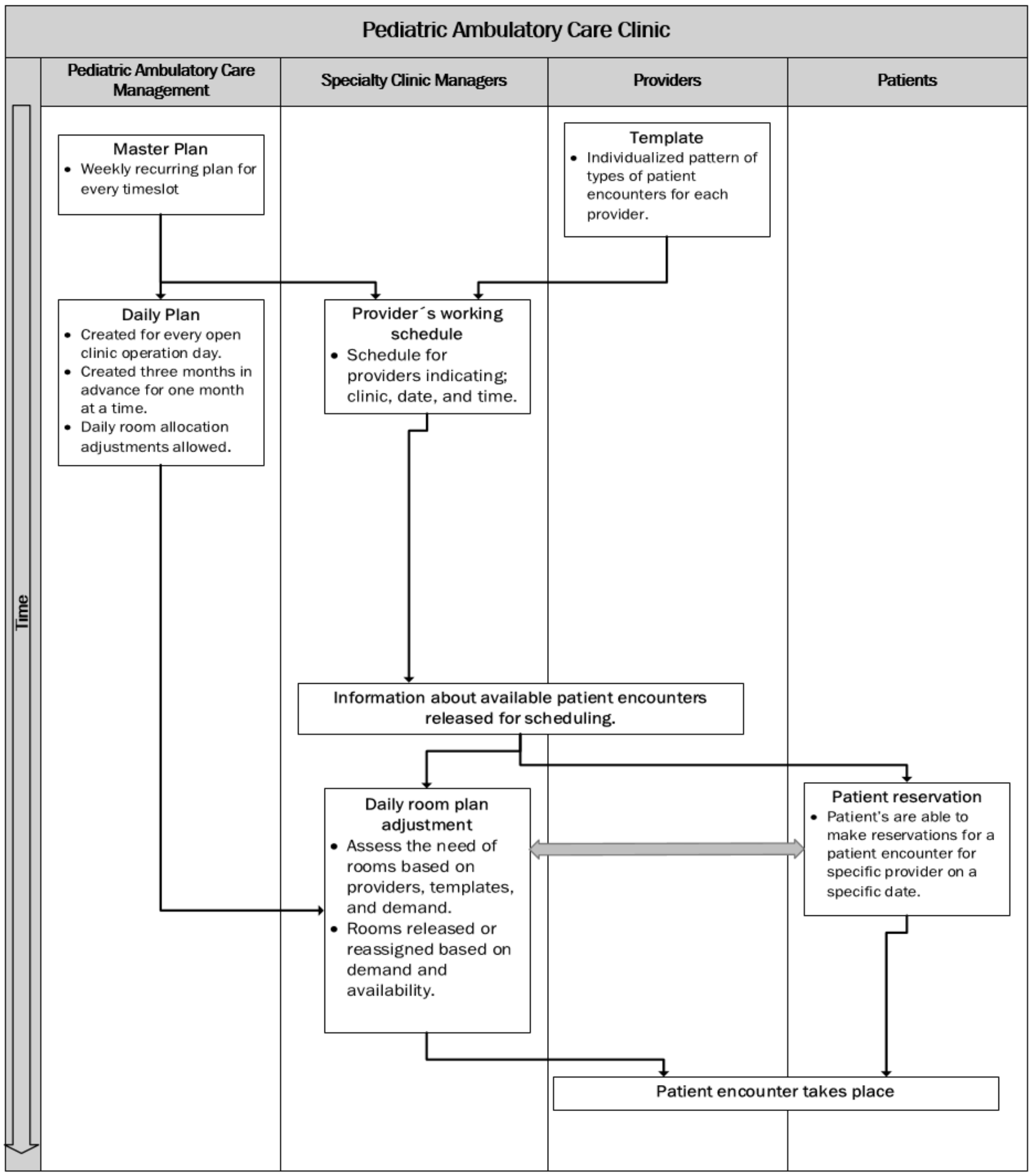

Figure 3.1: Flow of current process of room allocation at Seattle Children's Hospital outpatient pediatric ambulatory care clinic.

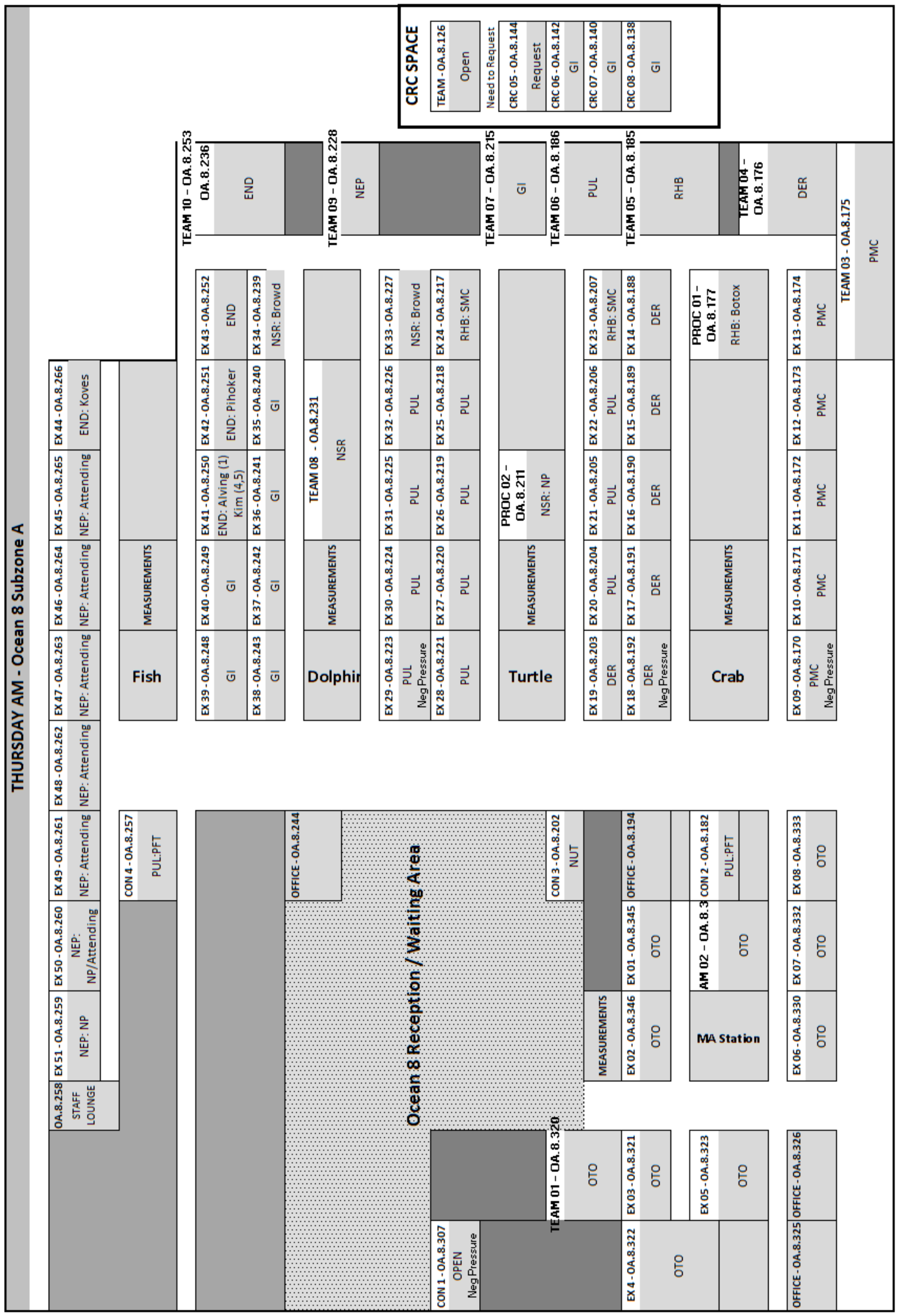

Figure 3.2: The master plan for a Thursday AM time slot.

Clinic ID	Clinic name
DER	Dermatology
GI	Gastroenterology
NEP	Nephrology
NSR	Neurosurgery
RHB	Rehabilitation

Table 3.1: Table showing sample of specialty clinic letter identification and corresponding name.

H=Hold O=Open R=Reassign T=Trade	AM PM	LOC	Room #	Original Allocated To Clinic	Assigned To Clinic	Provider / Comments	Outdate Received	Released 30 + Days Y/N	Released 60 + Days Y/N	Released 90 + Days Y/N
	AM	OA.8	Ex 16	NEP	NEP					
	AM	OA.8	Ex 17	NEP	NEP					
	AM	OA.8	Ex 18	NEP	NEP	**NEP:** Negative Pressure				
	AM	OA.8	Ex 19	DER	DER					
R	AM	OA.8	Ex 20	NEP	DER		03.14.14	Y	N	N
O	AM	OA.8	Ex 21	NEP	NEP		03.14.14	Y	Y	N

Figure 3.3: The daily plan for the specialty clinics created from the master plan.

seen in Figure 3.3, serves as a working document for the specialty clinic managers. A room that is not needed by a specialty clinic is labeled “Open” using the letter O, by the specialty clinic manager. The managers of the outpatient pediatric ambulatory care clinic keep track of when each change in room allocation is made and therefore let the specialty clinic managers record the date of change. If a specialty clinic is in need of more rooms than it has been allocated, the specialty clinic managers inspect the daily plan and look for rooms that have been labeled “Open” and reallocates it to their specialty clinic, changing the label to “Reassigned” using the letter R and changing the room label to the reassigned specialty clinic.

Each provider has a customized template, as seen in Figure 3.4. The template indicates types of patient encounters the provider will service and the sequence of the patient encounters throughout the time slot. For identification purposes this thesis uses a specific labeling system for the encounters where they are labeled by three

GI2, Templates

Contact person: ____________________

Contact phone #: ____________________ Date Range: ____________

Department/Unit: ______GI2______________ Block types: NV=60 RV=30

Comments or specify individual dates for the templates below:

	Thu AM
	Seattle
1st wk	
2nd wk	
3rd wk	
4th wk	
5th wk	
Weekly	
	*see dates
Start:	800am
Stop:	1200pm
800	RV (GI2.01)
815	
830	
845	
900	NV (GI2.02)
915	
930	
945	
1000	RV (GI2.03)
1015	
1030	
1045	
1100	NV (GI2.04)
1115	
1130	
1145	
1200	

NEP1,Templates

Contact person: ________________

Contact phone #: __________________ Date Range: ____________

Department/Unit: ________NEP___________ Block types: NV/RV = 60 min

Comments or specify individual dates for the templates below:

	Thu AM
	Seattle
1st wk	
2nd wk	
3rd wk	
4th wk	
5th wk	
Weekly	
	*see specific dates
Start:	08:00
Stop:	12:00
800	RV (NEP1.01)
810	
820	NV (NEP1.02)
830	
840	
850	
900	RV (NEP1.03)
910	
920	RV (NEP1.04)
930	
940	NV (NEP1.05)
950	
1000	
1010	
1020	NV (NEP1.06)
1030	
1040	
1050	
1100	RV (NEP1.07)
1110	
1120	RV (NEP1.08)
1130	
1140	UV (NEP1.09)
1150	
1200	

Figure 3.4: A sample of two templates, the left template is for Provider 2 at the Gastroenology (GI) clinic and the template on the right is for Provider 1 at the Nephrology (NEP) clinic.

factors; specialty clinic abbreviation, provider number within the specialty clinic, and finally the encounter number for the provider. For example, DER1.02 represents the second patient encounter of the day for provider 1 at the Dermatology clinic. Most common types of visits are: new visit patient (NV), return visit patient (RV), urgent visit patient (UV), and post/pre operation procedure (POP). Most providers estimate different durations for different types of patient encounters. A longer duration is usually estimated for new visit patient encounters, since additional time is needed for recording patient history and symptoms. Some of the service provided to the patient can be done by personnel with lower level of medical training such as a medical assistant, that allows the provider to have two patient encounters overlap in their schedule and therefore saves a lot of the provider's valuable time. Two rooms are needed in such cases for a single provider. The overlap in patient encounters are usually ongoing for only a short duration, which creates a gap in the room's schedule, where the room is not being used and a valuable resource gets wasted. Figure 3.5 demonstrates a schedule where patient encounters overlap, creating gaps in the room schedule.

Information about the provider's template and clinic dates are sent to the schedulers in order for patients to make an appointment. A centralized scheduling service is used for the entire hospital, for patients to make an appointment with a specific provider.

3.2 Statement of Problem

As seen in Figure 3.5, which represents five clinic rooms that have been allocated with the current room allocation method during a morning slot, a lot of the time the room is not in use is due to the arrangement of patient encounters in the templates. Note in the figure that patient encounters NEP1.07 and NEP1.08 are equal in duration to the prior NEP1 patient encounters, they however extend outside the four hour time slot and are therefore not shown in full length. Each room is only being used by one specialty

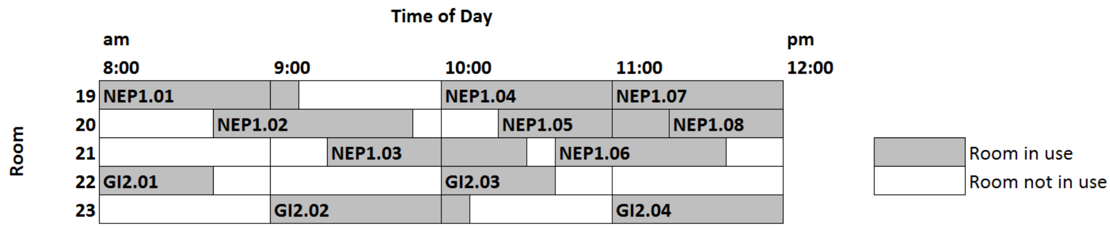

Figure 3.5: Example schedule for five rooms. Patient encounters for a single provider overlap, creating gaps in the room schedule.

clinic for every time slot and a lot of time is being wasted in the room's schedule. An observation made at the outpatient pediatric ambulatory care clinic, where an eight week period was examined for the five specialty clinics in Table 3.1 revealed that the combination of the number of rooms scheduled to each specialty clinic and the templates that were used by the providers only offered a 46.7% utilization of the room time. Furthermore, the template utilization, or the utilization of available patient encounters that were available to patients, was only 79%, which further reduced the utilized room time to 36.9%.

In order to reduce the number of rooms used and increase the efficient use of the rooms, a method to share rooms between the specialty clinics within each time slot was created. Instead of allocating a room to a single specialty clinic for an entire time slot, patient encounters are allocated to a room for the estimated duration of the patient encounter. By taking advantage of different starting time and duration of patient encounters between specialty clinics, the optimization methodology reduces the gaps in the room schedule and fewer rooms are needed to accommodate the scheduled patient encounters.

3.3 Metrics of Performance

Several metrics are observed to evaluate the performance of the system. To compare the proposed method of room allocation to the current method the metrics have to be equally applicable for evaluating the performance.

Number of Rooms

This study focuses on reducing the number of rooms needed to accommodate all scheduled patient encounters. For system performance we measure the number of rooms allocated.

Room Utilization

Since the number of patient encounters will not change, the room utilization will increase as the number of rooms is decreased. The utilization factor is based on time and is shown in (3.1),

$$\frac{\textit{Room time occupied by patients}}{\textit{Total room time available}} = \textit{Room utilization.} \tag{3.1}$$

For example, a weekly utilization was estimated using data from an eight week period. The average weekly room time occupied by patients was 301.03 hours, and the average weekly room time available was 675.52 hours. Using the formula the average weekly room utilization was 46.7%.

Patient Waiting Time

To examine how different methods of room allocation affect the patients, we look at the patient's waiting time for an available room. This metric is estimated by using the simulation model described in section 3.5.

3.4 Optimization Model

3.4.1 First Phase - Minimizing Number of Rooms Using Current Template

The objective of the optimization model is to allocate all the patient encounters to as few rooms as possible, using a binary optimization programming model. To manipulate the model to use as few rooms as possible we introduce weighted cost to the rooms, which increase with each room, such that room 1 has a cost of one, room 2 has a cost of two and so forth. The model tries to allocate the encounters to the cheapest rooms available, therefore minimizing the number of rooms needed. Information of starting time and duration of each patient encounter is collected from the template of the providers that are scheduled to see patients. The model input represents information from the provider templates, such as seen in Figure 3.4, and can be seen in Table 4.2.

Data Given

n: number of rooms available
m: number of patient encounters
T: number of time intervals in one slot (e.g., $T = 48$ where the time intervals are five minutes and the time slots are four hours)
S_k: starting time interval for patient encounter k, for all $k = 1, \ldots, m$
W_k: duration of patient encounter k in time intervals, for all $k = 1, \ldots, m$
C_j: weighted cost factor for room j, for all $j = 1, \ldots, n$

For our test case we have 23 rooms ($n = 23$) that need to be allocated to five specialty clinics with a total of 65 patient encounters ($m = 65$) that have to be seen within one four hour time slot that contains 48, five minute, time intervals ($T = 48$).

An additional ten minutes, or two time intervals will be added to each patient encounter to reflect room cleanup and preparation time. The added time is considered a time that the room is still unavailable once the patient encounter has finished. A ten minute addition is assumed to represent all the room time needed to cleanup and prepare for another patient in all cases.

Decision Variables

The optimization model uses two types of binary decision variables for its calculations; x_{jk} and r_{jkt}. The x_{jk} variable keeps record of the location of each patient encounter. This information is used by the algorithm to calculate the total cost of the rooms and to reserve room time for the duration of the patient encounter. Let

$$x_{jk} = \begin{cases} 1, & \text{if patient encounter } k \text{ is assigned to room } j \\ 0, & \text{otherwise} \end{cases}$$

for all $j = 1, \ldots, n$, and $k = 1, \ldots, m$.

The r_{jkt} variable is time dependent. It therefore creates a schedule for the rooms over the course of the whole time slot. The variable makes it easy to ensure that no two patient encounters are located at the same time in the same room. Let

$$r_{jkt} = \begin{cases} 1, & \text{if room } j \text{ is used for patient encounter } k \text{ at time interval } t \\ 0, & \text{otherwise} \end{cases}$$

for all $j = 1, \ldots, n$, $k = 1, \ldots, m$, and $t = 1, \ldots, T$.

Objective Function

The objective function minimizes the weighted cost of the rooms. By multiplying the cost of each room with the number of encounters in each room the model tries to allocate every patient encounter to the cheapest available room,

$$Minimize \sum_{j=1}^{n} C_j(\sum_{k=1}^{m} x_{jk}). \tag{3.2}$$

Model Constraints

The first constraint, shown in (3.3), ensures that every patient encounter k is allocated to exactly one room,

$$\sum_{j=1}^{n} x_{jk} = 1, \quad \text{for all } k. \tag{3.3}$$

To allocate patient encounter k in the time schedule we need to reserve time in r_{jkt} from the starting interval S_k, for the duration W_k of the patient encounter. By summing over time in r_{jkt} from S_k to $S_k + W_k - 1$ the model reserves a time equal to W_k at the location designated by x_{jk}. We deduct 1 from the upper limit of the sum since S_k and the first time interval in W_k represent the same time interval and is therefore counted twice. This constraint is shown in (3.4),

$$\sum_{t=S_k}^{S_k+W_k-1} r_{jkt} = W_k * x_{jk}, \quad \text{for all } j \text{ and } k. \tag{3.4}$$

To make sure that the reserved time intervals in r_{jkt} are exactly as many as the combined duration intervals of the patient encounters, we match the two sums in (3.5),

$$\sum_{k=1}^{m} W_k = \sum_{j=1}^{n} \sum_{t=1}^{T} \sum_{k=1}^{m} r_{jkt}. \tag{3.5}$$

Finally we make sure that no more than one patient encounter k is scheduled in every room j,

$$\sum_{k=1}^{m} r_{jkt} \leq 1, \quad \text{for all } j \text{ and } t. \tag{3.6}$$

The two variables, x_{jk} and r_{jkt}, are both constrained to a binary value of either 0 or 1.

3.4.2 Second Phase - Equal Allocation Using Current Template

Due to the cost factor that is used to minimize the number of rooms, the allocation of patient encounters is not equal between the rooms, hence the optimization model is prone to allocate more patient encounters to rooms with lower weighted cost. From the first phase model we now know the minimum number of rooms needed to accommodate the patient encounters and are able to create a second phase optimization model which can distribute the patient encounters equally to the rooms. For our second phase optimization model we use the result of the minimum number of rooms from the first phase model as our new number of available rooms. By adjusting the optimization model with the new minimum number of rooms needed, we can change the objective of the model to allocate patient encounters to the rooms in order to minimize the difference in utilization between rooms.

Data Given

For the second phase optimization model we use all the same input data from the first phase model except the weighted cost factor C_j.

n: number of rooms (set to the value obtained in the first phase optimization model)
m: number of patient encounters
T: number of time intervals in one slot (e.g., $T = 48$ where the time intervals are five minutes and the time slots are four hours)
S_k: starting time interval for patient encounter k, for all $k = 1, \ldots, m$
W_k: duration of patient encounter k in time intervals, for all $k = 1, \ldots, m$

Decision Variables

In addition to x_{jk} and r_{jkt} we introduce two new decision variables which we use to balance the utilization of the rooms,

U_{Max}: the maximum utilization of the used rooms,
U_{Min}: the minimum utilization of the used rooms.

Objective Function

The new objective function minimizes the difference in the maximum and minimum utilization of the rooms,

$$\textit{Minimize } U_{Max} - U_{Min}. \tag{3.7}$$

Constraints

The second phase model uses constraints shown in (3.3), (3.4), (3.5), and (3.6) from the first phase optimization model. Two new constraints are introduced, to provide the upper and lower bounds on the utilization, U_{Max} and U_{Min}. By calculating the used room time for each room we constrain the value of U_{Max} to be greater than or equal to the used room time for all the rooms and the value of U_{Min} to be less than or equal to the used room time of all the rooms,

$$\sum_{k=1}^{m} \sum_{t=1}^{48} r_{jkt} \leq U_{Max}, \qquad \text{for all } j, \tag{3.8}$$

$$\sum_{k=1}^{m} \sum_{t=1}^{48} r_{jkt} \geq U_{Min}, \qquad \text{for all } j. \tag{3.9}$$

The second phase model gives a much more balanced utilization between the rooms, minimizing the difference in utilization between the rooms.

3.4.3 New Template Generated With Optimization

Currently the allocation is constrained by the starting time (S_k) and duration (W_k) of patient encounters provided by the individual templates created by the providers. The duration represents the patient encounters and indicates its type, however by allowing the starting time for the appointment to be moved, it is possible to rearrange the sequence of the patient encounters and therefore create a possible improvement in the room allocation. By doing so we keep the same types of appointments as in the original templates but rearrange them and create new templates with new starting times that have been optimized in order to increase the utilization of the rooms. Since some of the providers choose to have their patient encounters overlap we need to take into account that the patient encounters of the same provider can partially overlap.

Data Given

n: number of rooms available

m: number of patient encounters

l: number of providers

T: number of time intervals in one slot ($T = 50$ where the time intervals are five minutes and the time slots are four hours), two extra intervals are added to allow additional cleanup and preparation time for each patient encounter

W_k: duration of patient encounter k in time intervals, for all $k = 1, \ldots, m$

B_k: duration of pre-inspection before interacting with doctor of patient encounter k in time intervals, for all $k = 1, \ldots, m$

D_k: duration of provider interaction of patient encounter k in time intervals, for all $k = 1, \ldots, m$

E_k: duration of post inspection after interacting with doctor of patient encounter k in time intervals, for all $k = 1, \ldots, m$

Note:($W_k = B_k + D_k + E_k$)

P_{ki}: binary matrix, 1 if provider i attends patient encounter k, else 0

C_j: weighted cost factor for room j, for all $j = 1, \ldots, n$

We use the same test case as before where 5 specialty clinics have 23 rooms ($n = 23$) to allocate 65 patient encounters ($m = 65$) for a single 4 hour time slot that contains 48, 5 minute, time intervals, with two extra time intervals for the added clean up time ($T = 50$). We also have 10 providers ($i = 10$) that work in these 5 specialty clinics.

Decision Variables

This version of the model uses three types of binary decision variables; a_{jkt}, y_{js} and z_{is}.

The first decision variable is a_{jkt} and serves a similar purpose as r_{jkt} from the prior second phase model. It creates one time schedule for all encounters and rooms,

$$a_{jkt} = \begin{cases} 1, & \text{if patient encounter } k \text{ starts at time interval } t \text{ and is assigned to room } j \\ 0, & \text{otherwise} \end{cases}$$

for all $j = 1, \ldots, n$, $k = 1, \ldots, m$ and $t = 1, \ldots, T$.

The variable y_{js} creates a schedule for the rooms, indicating starting intervals of each patient encounter that is allocated to each room. The variable indicates which encounter goes into which room,

$$y_{js} = \begin{cases} 1, & \text{if room } j \text{ has a patient encounter starting at time interval } s \\ 0, & \text{otherwise} \end{cases}$$

for all $j = 1, \ldots, n$, and $s = 1, \ldots, T$.

The variable z_{is} creates a time schedule for each provider, preventing unwanted overlap of patient encounters,

$$z_{is} = \begin{cases} 1, & \text{if provider } i \text{ attends a patient encounter starting at time interval } s \\ 0, & \text{otherwise} \end{cases}$$

for all $i = 1, \ldots, l$, and $s = 1, \ldots, T$.

Objective Function

As in the first model, the objective function minimizes the weighted cost of each room, forcing the model to use as few rooms as possible,

$$Minimize \sum_{j=1}^{n} C_j(\sum_{s=1}^{T} y_{js}). \tag{3.10}$$

Model Constraint

The first constraint, shown in (3.11), makes sure that every encounter is allocated to a single room, with exactly one starting time,

$$\sum_{j=1}^{n}\sum_{t=1}^{T} a_{jkt} = 1, \quad \text{for all } k. \tag{3.11}$$

The second constraint, shown in (3.12), makes sure that the total number of patient encounters allocated equals the total patient encounters scheduled,

$$\sum_{j=1}^{n}\sum_{t=1}^{T}\sum_{k=1}^{m} a_{jkt} = m. \tag{3.12}$$

To create the schedule for each room a “big M” is used, which represents a large number, such that when $a_{jkt} = 0$, then it neutralizes the constraint and makes it ineffective to the model, but when $a_{jkt} = 1$ the constraint makes sure that no other patient encounter starts in the same room for the duration of $W_k - 1$ time intervals,

$$(1 - a_{jkt}) * M \geq \sum_{s=t+1}^{t+W_k-1} y_{js}, \quad \text{for all } k, j \text{ and } t = 1, \ldots, T - W_k + 1. \tag{3.13}$$

Note that the range of t in (3.13) only spans time intervals one through $T - W_k + 1$, which is done so the patient encounter cannot start later than $T - W_k + 1$ or they would exceed the outpatient pediatric ambulatory care clinic opening time. In order to prevent that a patient encounter k never starts later than $T - W_k + 1$ we have constraint (3.14),

$$\sum_{t=T-W_k+1}^{T} a_{jkt} = 0, \quad \text{for all } k \text{ and } j. \tag{3.14}$$

In order to place a patient encounter to the room schedule we have,

$$\sum_{k=1}^{m} a_{jks} = y_{js}, \quad \text{for all } j \text{ and } s. \tag{3.15}$$

Constraint (3.16) prevents two or more patient encounters from starting at the same time interval in the same room,

$$\sum_{k=1}^{m} a_{jkt} \leq 1, \quad \text{for all } j \text{ and } t. \tag{3.16}$$

To prevent an unwanted overlap in the providers schedule a “big M” is again used, and the parameter P_{ki} is added to link multiple patient encounters to a single provider

i,

$$(1 - (a_{jkt} * P_{ki})) * M \geq \sum_{s=t+B_k+1}^{t+B_k+D_k-1} z_{is}, \quad \text{for all } i,\ k,\ j, \text{ and } t = 1, \ldots, T - D_k + 1. \tag{3.17}$$

The following constraint is used to create the provider's schedule,

$$\sum_{t=s-B_k}^{s-B_k} \sum_{j=1}^{n} a_{jkt} * p_{ki} = z_{is}, \quad \text{for all } i,\ k, \text{ and } s = B_k, \ldots, T. \tag{3.18}$$

3.4.4 Optimization Model Interaction

For the second phase optimization model to generate a room schedule that minimizes the difference in utilization between the rooms, results are needed from either the first phase optimization model or the model generating new templates using optimization. The interaction is explained in Figure 3.6.

3.5 Simulation of Performance

The optimization model assumed that the starting times and duration of patient encounters are deterministic. However, in the real world they are uncertain, and that does affect the behavior and performance of the system. In order to examine the behavior and performance of the system using the proposed room allocation method in contrast to the current room allocation method a simulation model is created, that contains uncertainty to represent the variability of the real world.

To get an accurate comparison, models representing both methods are tested using the same variability for activities that are considered to be critical for the system. Arrival times and actual patient encounter duration are two uncertainty factors that have been identified to affect the performance metrics of patient waiting time for an empty room. The simulation model monitors the number of patients that have to wait for an available room past their scheduled patient encounter starting time and their

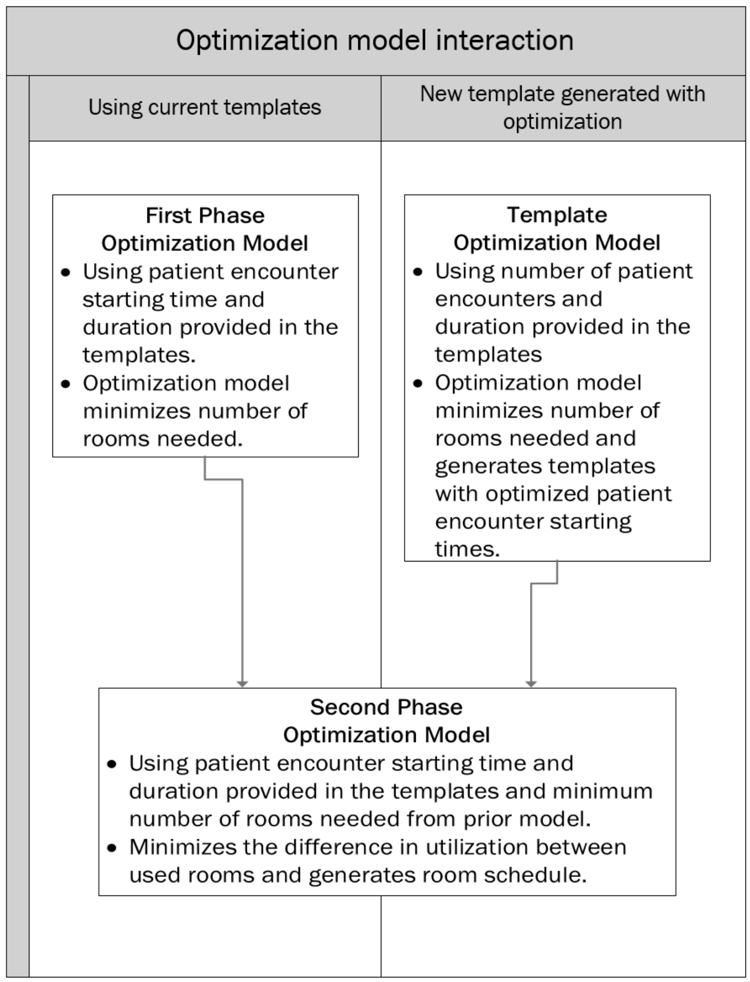

Figure 3.6: Connection between the three optimization models, either the First Phase Optimization Model or Template Optimization is used as input for the Second Phase Optimization Model.

waiting time. Three different scenarios are tested: 1) current allocation method; 2) proposed allocation where patient encounters are directed into specific rooms decided by the two-phase optimization model; 3) using the least number of rooms proposed by the optimization model, the patient encounters occupy the next available room in a first-in-first-out (FIFO) sequence.

The structure of the simulation model components for all three scenarios are similar. The patients, presented as entities, enter the system to get service. Each patient has an attribute that determine their arrival time, patient encounter ID and patient encounter duration. The patients go past a check-in server which is assumed not to take more than one minute; we assume that five check-in counters are available to the specialty clinics tested in the model. The patients travel to a room that is presented as servers, their service time in the room is determined by the patient encounter duration attribute. While a patient is being serviced in a room, the room is occupied and no other patient can get service at the same time in the same room. If any other patient enters the system to get service before the prior has finished service, the latter patient has to wait for the room to be available. When the service time for each patent is over the patient leaves the room and exits the system, allowing the room to be occupied by other patients. Patient waiting time for an available room and the room utilization are monitored.

In the first scenario, there is one server for each specialty clinic. The capacity of each server is the number of rooms each specialty clinic is originally allocated by the current method. The scenario is shown in Figure 3.7. When a patient arrives at the outpatient pediatric ambulatory care clinic, the medical assistant shows the patient to the next available room that has been allocated to the specialty clinic. If all of the rooms are occupied the patient has to wait until one becomes available.

In the second scenario, each server represents a specific room, and an attribute is set to indicate which room the patient encounter is scheduled to go to. The scenario is shown in Figure 3.8. The allocation schedule is provided by the two-phase

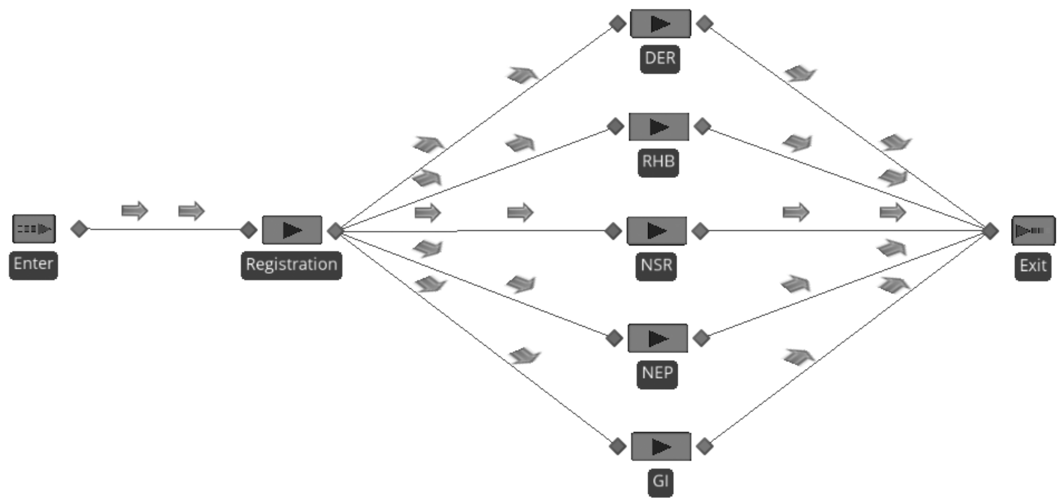

Figure 3.7: Setup of the first simulation scenario.

optimization model. When a patient arrives to the outpatient pediatric ambulatory care clinic and the allocated room is occupied by a previous patient, the patient waits until the room becomes available.

The third scenario only contains one server that represents all the clinic rooms. The scenario is shown in Figure 3.9. The capacity of the server is set to be the minimum number of rooms indicated by the optimization model. The simulation model replicates a setup where the medical assistant shows each arriving patient to the next available clinic room. If a patient arrives when all rooms are occupied the patient will wait until any room becomes available, then is shown to that room.

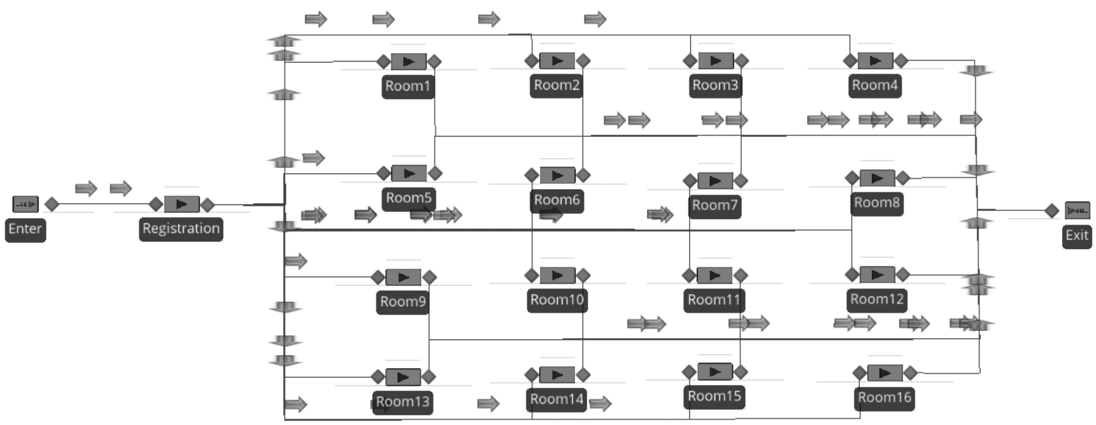

Figure 3.8: Setup of the second simulation scenario.

Figure 3.9: Setup of the third simulation scenario.

Chapter 4

OPTIMIZATION AND SIMULATION RESULTS

4.1 Input Data

To test the model with actual data from the outpatient pediatric ambulatory care clinic at Seattle Children's Hospital, a time slot was chosen and data collected from the specialty clinics. Due to the large amount of data, a subset of 5 specialty clinics, which all had relatively many patient encounters at the same time, was chosen. The five specialty clinics, Dermatology (DER), Gastroenterology (GI), Nephrology (NRP), Neurosurgery (NSR), and Rehabilitation (RHB), have in total 65 patient encounters that are being seen by 10 providers in 23 clinic rooms on a specific Thursday AM time slot. The daily room plan provided information on the actual number of rooms allocated and can be seen in Table 4.1. The starting time and duration of patient encounters was collected from the templates of all of the 10 providers, and every patient encounter was given a specific ID, as seen in Table 4.2.

Clinic	Number of rooms
Dermatology (DER)	5
Gastroenterology (GI)	9
Nephrology (NEP)	3
Neurosurgery (NSR)	3
Rehabilitation (RHB)	3

Table 4.1: The number of rooms allocated to each specialty clinic for the chosen Thursday morning time slot.

The two time interval addition for room cleanup and preparation time and has not been added to the patient encounter duration in Table 4.2; the two time intervals

Encounter $\langle k \rangle$	Starting Interval $\langle S_k \rangle$	Duration in Intervals $\langle W_k \rangle$	Encounter $\langle k \rangle$	Starting Interval $\langle S_k \rangle$	Duration in Intervals $\langle W_k \rangle$
DER1.01	1	4	GI2.04	37	12
DER1.02	5	4	GI3.01	3	6
DER1.03	9	4	GI3.02	9	6
DER1.04	13	4	GI3.03	15	6
DER1.05	17	4	GI3.04	21	6
DER1.06	21	4	GI3.05	27	6
DER1.07	25	4	GI3.06	33	6
DER1.08	29	4	GI3.07	39	6
DER1.09	33	4	GI3.08	45	6
DER1.10	37	4	GI4.01	13	6
DER1.11	41	4	GI4.02	37	6
DER2.01	1	4	NEP1.01	1	12
DER2.02	5	4	NEP1.02	5	12
DER2.03	9	4	NEP1.03	13	12
DER2.04	13	4	NEP1.04	17	12
DER2.05	17	4	NEP1.05	21	12
DER2.06	21	4	NEP1.06	29	12
DER2.07	25	4	NEP1.07	37	12
DER2.08	29	4	NEP1.08	41	8
DER2.09	33	4	NEP1.09	45	4
DER2.10	37	4	NSR1.01	1	8
DER2.11	41	4	NSR1.02	9	8
DER3.01	8	4	NSR1.03	17	8
DER3.02	20	4	NSR1.04	25	4
DER3.03	31	4	NSR1.05	29	4
GI1.01	4	9	NSR1.06	33	4
GI1.02	13	9	NSR1.07	37	8
GI1.03	22	9	NSR1.08	45	4
GI1.04	31	9	RHB1.01	1	12
GI1.05	40	9	RHB1.02	13	12
GI2.01	1	6	RHB1.03	25	12
GI2.02	13	12	RHB1.04	37	12
GI2.03	25	6			

Table 4.2: The 65 patient encounters, identified by specialty clininc and provider number, with starting time interval and duration (in time intervals).

are added to every patient encounter duration except those who finish at the last two time intervals (time intervals 47 and 48). In such cases, the turnaround and cleanup time extend past the 4 hour time slot where patient encounter scheduling has stopped. This additional time also brings flexibility to the patient encounter duration when the actual duration of the patient encounter exceeds the estimated time.

The room schedule is presented, with the 10 minute additional time, in Figure 4.1. No historical data exists for the actual room allocation, but according to room availability and patient encounter duration time demand, and by observing the specialty clinics, the presented allocation is similar to the actual allocation.

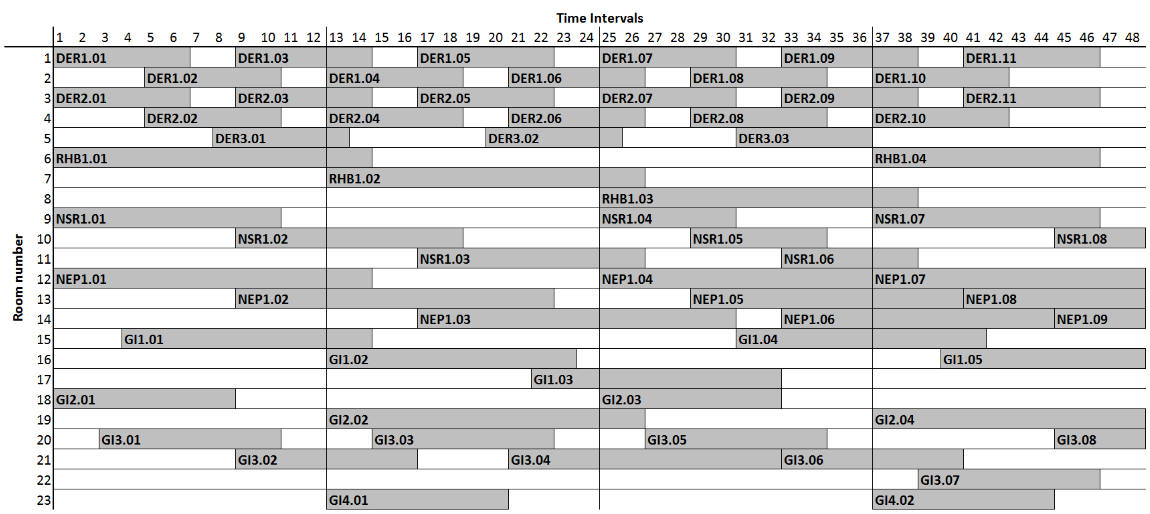

Figure 4.1: Current allocation of clinic rooms and schedule of patient encounters.

4.2 *Optimizing Room Allocation Using Current Templates*

The first phase optimization model, as expected, allocated most patient encounters to room number one, second most in room number two, and so on, as illustrated in Figure 4.2. The minimum number of rooms needed to accommodate all the patient encounters, with the starting time and duration provided by the templates and the additional 10 minute turnaround time, is 16 rooms, which is 7 rooms less than the

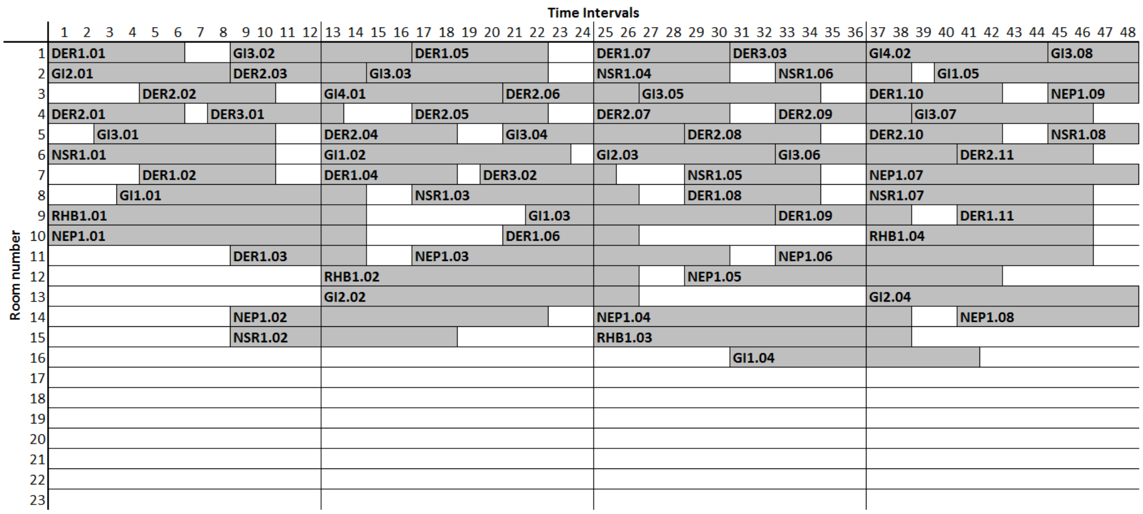

Figure 4.2: First phase room allocation of patient encounters using weighted cost factor for the room and minimizing the number of rooms.

current allocation method uses. By reducing the needed rooms by 30.4% the room utilization increases from 39.2% to 56.4%.

As seen in Figure 4.2 room number one has only 4 time intervals, or twenty minutes, free while room sixteen has 37 free time intervals, or three hours and five minutes, which is over nine times more of unoccupied time. To create a schedule where the difference in occupied room time is minimized, the second phase optimization model uses the minimum number of rooms, 16 rooms, from the phase one model as input data to the phase two optimization model.

The result of the second phase model can be seen in Figure 4.3, where the difference between the room with the most free time and the room with the least free time is one time interval. The rooms with the most free time are occupied for 33 time intervals while the room with the least occupied free time are occupied for 34 time intervals. Table 4.3 shows the room schedule for the patient encounters as optimized by the second phase model.

Patient encounter $\langle k\rangle$	Room number $\langle j\rangle$	Patient encounter $\langle k\rangle$	Room number $\langle j\rangle$	Patient encounter $\langle k\rangle$	Room number $\langle j\rangle$
DER1.01	1	DER3.01	12	NEP1.01	9
DER1.02	4	DER3.02	3	NEP1.02	13
DER1.03	2	DER3.03	15	NEP1.03	9
DER1.04	3	GI1.01	10	NEP1.04	13
DER1.05	14	GI1.02	15	NEP1.05	3
DER1.06	16	GI1.03	7	NEP1.06	5
DER1.07	14	GI1.04	10	NEP1.07	16
DER1.08	1	GI1.05	7	NEP1.08	14
DER1.09	9	GI2.01	3	NEP1.09	1
DER1.10	2	GI2.02	6	NSR1.01	6
DER1.11	4	GI2.03	11	NSR1.02	16
DER2.01	2	GI2.04	8	NSR1.03	2
DER2.02	5	GI3.01	7	NSR1.04	15
DER2.03	14	GI3.02	11	NSR1.05	16
DER2.04	1	GI3.03	12	NSR1.06	7
DER2.05	11	GI3.04	10	NSR1.07	15
DER2.06	1	GI3.05	8	NSR1.08	10
DER2.07	12	GI3.06	14	RHB1.01	8
DER2.08	2	GI3.07	12	RHB1.02	5
DER2.09	12	GI3.08	11	RHB1.03	4
DER2.10	1	GI4.01	4	RHB1.04	6
DER2.11	13	GI4.02	11		

Table 4.3: Table showing the optimized room schedule using the two phase optimization model.

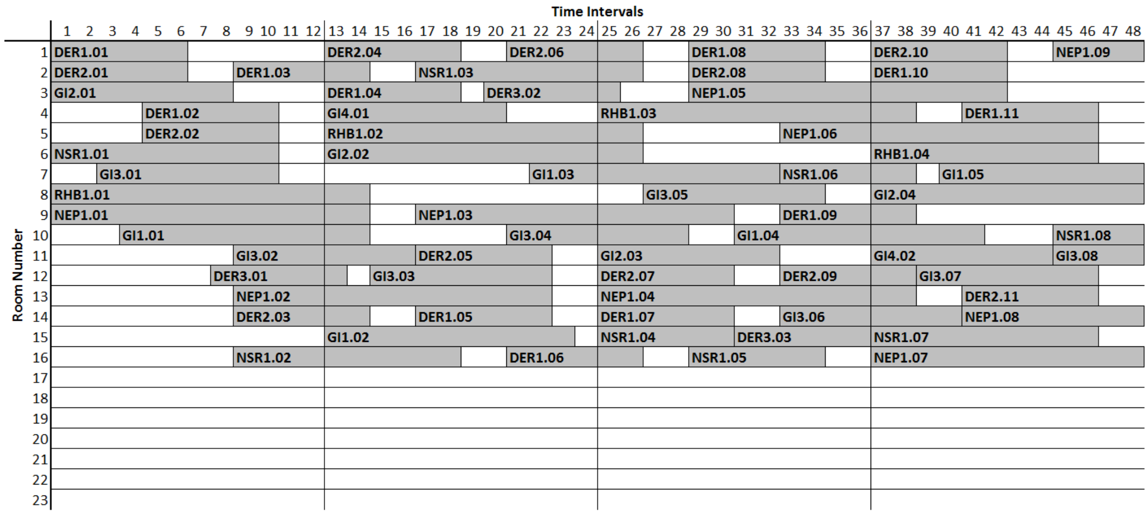

Figure 4.3: Second phase room allocation of patient encounters using the minimum number of rooms from the first stage model and allocating the patient encounters equally to the rooms.

4.3 Generating New Templates With Optimization

Using the optimization model presented in section 3.4.3, the optimization of the room allocation and the patient encounter starting time requires only the number of patient encounters per provider and their duration. The two time interval addition to each encounter is added for room turnaround time and is considered to be post-inspection duration that does not require the provider's attendance.

Due to the massive number of possible combinations and computational limitation, only a small subset of the test case could be run with the optimization model in under three hours. A Dell XPS ultra-book with 2.40 GHz Intel Core-i7 using the software AIMMS version 3.13, was used to run the model. Three providers were chosen for the subset; DER3, GI1, and RHB1. Table 4.4 presents the complete set of patient encounters and their duration. Since the purpose of the model is only to demonstrate improvements in minimizing number of rooms, a first phase optimization model is run to determine the minimum number of rooms, but the second phase optimization model is not necessary.

Patient encounter $\langle k \rangle$	Patient encounter duration $\langle W_k \rangle$	Patient encounter pre-inspection duration $\langle E_k \rangle$	Patient encounter provider interaction duration $\langle D_k \rangle$	Patient encounter post-inspection duration $\langle E_k \rangle$
DER3.01	6	0	4	2
DER3.02	6	0	4	2
DER3.03	6	0	4	2
GI1.01	11	0	9	2
GI1.02	11	0	9	2
GI1.03	11	0	9	2
GI1.04	11	0	9	2
GI1.05	11	0	9	2
RHB1.01	14	0	12	2
RHB1.02	14	0	12	2
RHB1.03	14	0	12	2
RHB1.04	14	0	12	2

Table 4.4: Table showing the data used for optimizing the providers template. Note that none of the selected patient encounters have pre-inspection duration, but the value is nevertheless shown.

In the current allocation method, these three providers used a total of seven rooms and had 31.25% utilization of room time. As a comparison, the first phase optimization model was run for the same specialty clinics using the provided starting time and duration of the patient encounters. The first phase optimization model determined the minimum number of rooms is 5 rooms, with a 43.75% utilization of room time.

By allowing the provider templates to be re-arranged, the result of the room allocation and patient starting time optimization gave a minimum number of 3 rooms, with a 72.92% utilization of room time. The optimized templates are shown in Figure 4.4 and the corresponding room schedule in Figure 4.5. Even though the order of the patient encounters is mixed, the identification of the patient encounters was arbitrary, and can easily be reordered.

Provider: **DER3**

Block type: NV/RV = 20 min

Thursday	
Specific date:	
Start:	8am
Stop:	12pm
800	NV/RV (DER3.03)
810	
820	
830	
840	
850	
900	
910	
920	
930	
940	
950	
1000	
1010	
1020	
1030	
1040	
1050	
1100	
1110	NV/RV (DER3.02)
1120	
1130	
1140	NV/RV(DER3.01)
1150	
1200	

Provider: **GI1**

Block type: NV/RV = 45 min

Thursday	
Specific date:	
Start:	8am
Stop:	12pm
800	RV (GI1.04)
815	
830	
845	NV (GI1.01)
900	
915	
930	NV (GI1.03)
945	
1000	
1015	RV (GI1.02)
1030	
1045	
1100	
1115	RV (GI1.05)
1130	
1145	
1200	

Provider: **RHB1**

Block type: NV/RV = 60 min

Thursday	
Specific date:	
Start:	8am
Stop:	12pm
800	NV (RHB1.04)
815	
830	
845	
900	RV (RHB1.03)
915	
930	
945	
1000	NV (RHB1.02)
1015	
1030	
1045	
1100	RV (RHB1.01)
1115	
1130	
1145	
1200	

Figure 4.4: New optimized templates for providers DER3, GI1, and RHB1.

Using the template optimization model to optimize patient encounter starting time shows substantial improvements from the current room allocation method and the proposed two phase optimization model. The level of improvements is based on the combination of patient encounters and providers that are being allocated at any given time.

4.4 Simulating the System Under Uncertainty

Simulating the system with uncertainty required time observation at the outpatient pediatric ambulatory care clinic where patient arrival times and patient encounter duration was sampled. Each clinic was sampled during one time slot. The time data was analyzed for arrival time of patient for all clinics, and for each individual patient encounter duration in the room until it became available again. An input analyzer

	Number of rooms used	Room utilization
For five clinics and ten providers:		
Current room allocation	23	39.2%
First phase optimization model	16	56.4%
For three clinics and three providers:		
Current room allocation	7	31.25%
First phase optimization model	5	43.75%
Template optimization model	3	72.92%

Table 4.5: Summary of optimization models results.

was used to determine the best fit distribution. Result for each sampling is shown in Table 4.6. Observations show that the scheduled time for a patient encounter duration is often shorter than the observed patient encounter durations. Such deviations will lead to an increase in patient waiting time for an available room.

Simulation experiments were run in the simulation software Simio, version 6, and number of replication for each setup was determined with a confidence level of a 95% statistical certainty for the combined total patient waiting time, and values were recorder for all replications.

The model runtime started one hour before the first schedule patient arrival in order to accept an early arrival of the first patients.

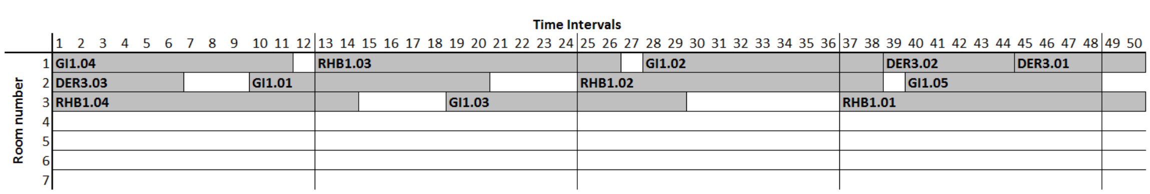

Figure 4.5: New optimized room schedule for providers DER3, GI1, and RHB1. Note that the additional 10 minutes for room turnaround go beyond the 4 hour time slot.

Input Data	**Probability distribution (minutes)**
Patient arrival time	$Arrivaltime + Normal(-9.53, 19.4)$
Dermatology (DER) 20 minute	$17.5 + Weibull(24.7, 1.69)$
Gastroenterology (GI) 30 minute	$Normal(42.5, 11.9)$
Gastroenterology (GI) 45 minute	$21.5 + 45 * Beta(0.544, 0.429)$
Gastroenterology (GI) 60 minute	$Normal(53.2, 13.8)$
Nephrology (NEP) 60 minute	$Normal(64.2, 15.9)$
Neurosurgery (NSR) 20 minute	$18.5 + Gamma(19.4, 0.797)$
Rehabilitation (RHB) 60 minute	$Normal(63.9, 13.9)$

Table 4.6: Probability distributions of input data for patient arrival and different patient encounter duration for all test case clinics. Normal distribution shows (mean value, standard deviation), Weibull distribution shows (shape factor, scale factor), Beta distribution shows (α_1,α_2), and Gamma distribution shows (α, β).

First Scenario

The simulation of the current allocation method required 549 replications to achieve a 95% statistical confidence level. For the time slot, up to six patients had to wait beyond their scheduled patient encounter starting time and up to four patient had to wait ten minutes or more. Longest recorded waiting time for an available room was 68 minutes.

Second Scenario

The second scenario uses information form the second phase optimization model, requiring only 40 replications to achieve 95% statistical confidence level. Up to 21 patient had to wait beyond their scheduled patient encounter starting time and up to 16 patient had to wait ten minutes or more. Longest recorded waiting time for an available room was 77 minutes.

Third Scenario

The third scenario only used the minimized number of rooms from the first phase optimization model, allowing the medical assistant to chose any available room when the patient arrived. The model needed 587 replication to achieve 95% statistical confidence level. Up to nine patients had to wait beyond their patient encounter starting time and only one patient had to wait longer than ten minutes. The longest recorded waiting time was eleven minutes.

Comparison of Performance of The Three Scenarios

Using a strict room allocation schedule from the second scenario results in the most patient waiting for an available room and for the longest time, while using the least number of room from our first phase optimization model in the third scenario results in the fewest patient waiting for an available room and for the least time.

By improving patient encounter duration a better allocation is available from the second phase model, however, by increasing the estimated patient encounter duration, more rooms might be required to meet the demand.

Chapter 5

SUMMARY AND FUTURE RESEARCH

5.1 Conclusion

The optimization models with simulated performance demonstrated improvements in clinic room utilization. Introducing a new model for allocating specialty clinics to clinic rooms by allocating each patient encounter to a specific room with the aid of a mathematical optimization modeling. The test case chosen included five specialty clinics and a Thursday AM time slot. When applying the new optimization model to the test case, the number of rooms was reduced from 23, to accommodate all the 65 patient encounters, to 16, increasing the effective utilized room time from 39.2% to 56.4%. The two phase optimization model creates a complete room schedule for the five specialty clinics where the difference in utilized room time is minimized between all of the rooms, creating an even workload to all the rooms.

Furthermore a template optimization model improved room utilization by including the patient encounter starting time in the optimization, creating an optimized room allocation and an optimized provider template. As a comparison, a the optimization model was run using the subset of specialty clinics with the patient encounter starting time to be able to evaluate the improvement in performance when including the patient encounter starting time in the optimization calculation. Using the current method the subset allocated 7 rooms with 31.25% room time utilization. Optimizing the room allocation with the two phase optimization model, using the patient encounters starting provided by the templates, decreased the number of rooms needed to 5 rooms and increased the room time utilization to 43.75%. Optimizing the room allocation with the template optimization model decreased the number of rooms even further and only required 3 rooms to accommodate all the patient encounters, increasing the room time utilized to 72.92%.

Simulating the performance of the system indicated that the proposed room allocation method would increase patient waiting time for an available room, primarily due to inaccurate patient encounter duration estimation from the templates and strict room allocation policy; not enough time is provided for many of the patient encounter is the room schedule. By sharing rooms, and assigning patients to rooms in a FIFO sequence. the patient maximum wait time was less than eleven minutes.

The improved room utilization demonstrates a clear example of the benefits using the proposed room allocation with the aid of a mathematical optimization model and by including more parameters in the optimization model, such as the patient encounter starting time, the performance of the clinic room continues to improve.

5.2 Limitations

The optimization and simulation models presented in this thesis were limited to a subset of five specialty clinics and on time slot. The performance of improvements of the two phase optimization model depends on the combination of templates scheduled for each time slot. Due to the high number of combinations and computational limitation, only three providers were modeled in the template optimization problem.

The proposed room allocation also has some limitations; the increased utilization will imply much stricter scheduling reducing the flexibility of the staff of each specialty clinic, such as the medical assistants and the providers, compared to the current room allocation method which provides more flexibility in allocating patient encounters and in increasing patient encounter duration. Moreover, an unforeseen increase in patient encounter duration could extend and overlap a following patient encounter in the same room. Such problem could lead to friction and conflicts between specialty clinics and reduce the level of quality of service to the patient.

5.3 Recommendations

This research provides the management team of the outpatient pediatric ambulatory care clinic with a tool to improve their room allocation methods in order to increase the room utilization by using less rooms than before while accommodating the same number of patient encounters. The rooms that will become available can be used to increase the number of patient encounters and help meet future demand.

Before implementing the proposed room allocation method a reevaluation of the patient encounters duration must be done in order to prevent increase in patient waiting time for an available room. As the observations made at the outpatient pediatric ambulatory care clinic revealed, most of the patient encounter duration exceeded their estimated duration. To increase the utilization of the rooms, an accurate patient encounter duration estimation policy must be in place where the total duration of the time when a room is occupied by a patient is estimated. While the estimation of the patient encounter duration remains inaccurate, running only the first phase optimization model is recommended to determine the minimum number of rooms needed to meet the demand. Then implement the room allocation in the third scenario of the simulation model, where the medical assistant will show the patient to the next available room.

The room allocation and the patient scheduling has a low tolerance for errors, since every patient encounter must have an available room at the scheduled time. Recommended first steps in implementing the new method would be to do a pilot by trying the proposed allocation method for two or three specialty clinics, but having extra rooms available in case of an overflow. Then gradually increase the specialty clinics being allocated together, eventually using the proposed allocation method for all of the specialty clinics that share the 55 clinic rooms at every single time slot.

5.4 Future Work

The initial work of optimizing patient encounter starting time with the template optimization model, demonstrated potential in further reducing the number of rooms needed, but also shows that computation is an issue in scaling up. In order to fully use the potential of generating new templates using optimization, a more efficient way of involving the patient encounters starting time in the optimization model must be developed or using computers with higher computational capability to create an optimized room allocation schedule with new patient encounter starting times for each time slot.

To improve the accuracy of the room allocation different methods can be introduced to reduce the unknown variability in the system. One such improvement is to reduce unexpected increase in the patient encounter duration. Such work has already been introduced at a limited experience by Beck (2010). Beck discusses ways of creating a history for every patient where prior visit are mapped and future patient encounter durations are estimated from prior patient encounter duration history.

Finally, a platform and a user interface has to be built to make the model easily available to the management of the outpatient pediatric ambulatory care clinic for daily use and a data set from every template has to be collected to be readily used by the two phase optimization model.

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