# A SIMULATION-IP BASED TOOL FOR PATIENT ADMISSION SERVICES IN A MULTI-SPECIALTY OUTPATIENT CLINIC

Travis Sowle Natalie Gardini Fernando Vazquez Arroyo Vazquez Eduardo Pérez Jesus A. Jimenez

Lenore DePagter

Ingram School of Engineering Texas State University 601 University Drive San Marcos, TX 78666, USA Live Oak Health Partners 1340 Wonder World Drive San Marcos, TX 78666, USA

### **ABSTRACT**

In this paper, we develop a framework that integrates a discrete-event simulation model and integer programming (IP) model for patient admission planning and the intermediate term allocation of resource capacities. Two types of patients are considered in this study: new and existing. The simulation model is used to find the best balance between new and existing patients arriving to each appointment time period during the day. New patients require more time to complete their admission processes and for visiting with a doctor. The IP produces an optimal calendar schedule for the doctors, i.e. the best appointment time for each doctor to see new patients. We report on computational results based on a real clinic, historical data, and both patient and management performance measures.

### 1 INTRODUCTION

Among others, patient waiting time for service is one of the major reasons for patient dissatisfaction in healthcare outpatient clinics. Typically, a patient will call the clinic in advance to set-up an appointment to visit with a doctor. Upon arrival to the clinic, most patients are required to go through a sequence of activities before seeing a physician. For instance, patients are required to check-in and complete some paperwork. The amount of paperwork the patient is required to complete depends on whether the patient visits the clinic for the first time or not. Patients visiting the clinic for the first time are considered new patients and need to complete more paper work than those patients that are already in the system. New patients also require more one-on-one help from the front desk staff, which subsequently creates queues in the system and limits the staff's ability to answer the phones promptly to set-up appointments. In addition to the check-in process, patients visit with a nurse before seeing a physician and return to the clinic's front desk in order to complete the check-out process. Most of the patients expect short service times and no queues when arriving to their appointment to see a doctor; otherwise, there will be patient dissatisfaction which impacts the clinic's quality of service.

The rise in healthcare costs in the U.S. has propelled the need to improve the efficiency of service in healthcare clinics. The literature is full of studies addressing topics such as reducing patient waiting times, patient scheduling, and resource management in healthcare clinics. However these studies exclude the details regarding the clinic's front desk services and operation. Usually a clinic is modeled as a single server and these models do not consider activities such as answering patient calls to set-up appointments, checkin and check-out processes, and patient documentation. Since physicians are only available during specif-

ic periods of time during the day, it is important to manage the front operations of the clinic efficiently to achieve the best utilization of these resources.

This paper builds upon the work by Mocarzel et al. (2013), where a discrete-event simulation was developed to model patient admission processes occurring at a multi-specialty outpatient clinic front desk with seven doctors. The simulation model captured the complexities and interactions occurring at the front desk. Based on a computational study the authors provided recommendations that resulted in a more balanced workload for the front desk staff and reduced the patient waiting time for check-in and check-out. The computational study showed that by balancing the number of new and existing patients arriving to the clinic at each appointment time period, the performance of the clinic can be improved by reducing the patient waiting time for check-in and check-out. However, the authors did not provide guidelines or rules to schedule the appointments at the clinic. In this paper, we develop a framework that integrates a discrete-event simulation model and integer programming (IP) for patient admission planning and the intermediate term allocation of resource capacities. The IP produces optimal daily schedules for the doctors, i.e. the best appointment times to see new patients for each doctor so that congestion at the front desk of the clinic is minimized.

The rest of the paper is organized as follows. In Section 2, we review closely related work. We provide a description of the problem in Section 3, and discuss the optimization scheduling model in Section 4. We report on a computational study in Section 5, and end the paper with some concluding remarks and recommendations for the operation of the front desk in Section 6.

### 2 RELATED WORK

Healthcare clinics are constantly looking for ways to improve their services and reduce cost. One of the most important measurements for quality of service is the patient waiting time. There are several sources of literature that illustrate how operations research techniques can be used to model and improve service operations and patient flow in healthcare. More specifically, simulation and mathematical models are useful tools when trying to understand and optimize these systems. For example, Ho and Lau (1992) and Ho et al. (1995) evaluated several appointment rules within different healthcare clinic environments; and found out that no rule was capable of improving all the performance measures for every clinic environment. Therefore, a heuristic was used to choose a rule depending on the distinctive nature of each environment.

Liu and Liu (1998a) and Liu and Liu (1998b) found and showed the similarities between the best performing appointment schedules by using a simulation model with multiple doctors and random arrival times. Robinson and Chen (2003) used a stochastic linear program to observe the system under different appointment rules. The model was used to optimize the scheduling times when a specific sequence of patients is to be followed. Cayirli et al. (2006) found that differing appointment rules have less of an effect on optimality than patient sequencing. This was concluded by studying patient characteristic and appointment system element interactions. LaGanga and Lawrence (2007) performed a computational study to estimate providers' overtime and patient waiting times. Their model represents a single provider with deterministic service times and a target overbooking level. They conclude that overbooking can lead to greater throughput without significantly higher waiting times. Gul et al. (2011) considers a multi-specialty outpatient procedure clinic. The authors use discrete event simulation to evaluate 12 different scheduling and appointment time setting heuristic, then uses a bi-criteria genetic algorithm to see if performance can be improved by changing the day when a procedure is scheduled. The paper does not consider the front desk resources. Pérez et al. (2010), Pérez et al. (2011), and Pérez et al. (2013) use simulation and optimization to schedule patients in nuclear medicine clinics while considering both patient and manager perspectives. Their results provide insights regarding resource allocation policies and patient admissions schedules.

This research differs from earlier studies in a number of ways. First, this work takes into account the operation of the clinic front desk clinic when scheduling patients. The goal is to minimize the waiting time at the clinic by balancing the number of new patients arriving at the same time for their check-in. Second, a multispecialty clinic is considered with multiple doctors with their independent schedules and preferences in terms of appointment durations. This is a highly constrained healthcare environment and the scheduling of patients in such an environment was classified by Gupta and Denton (2008) as a research open challenge.

### 3 PROBLEM DESCRIPTION

We consider a multispecialty clinic that has seven doctors: two orthopedics, three surgeons, one ear nose throat (ENT) doctor, and one audiologist. The availability of each doctor depends on the day of the week. For example some of the doctors might be available three days of the week while others might be available only half of the day on certain days of the week. Phone calls to schedule appointments for all doctors are managed by a centralized front desk with four staff members. The front desk staff is also in charge of checking-in and checking-out patients, collecting copays, scanning/filing documents, medical records, insurance/id cards, verifying benefits, distributing faxes, making copies, and verifying benefits for all the physicians the day before patient appointments. The outpatient clinic in this study has multiple issues related to patient admission and workflow. The main problems identified at the clinic are: 1) patient complaints about difficulty reaching anyone on the phone to schedule their appointments and 2) long waiting times to check-in and check-out of the clinic.

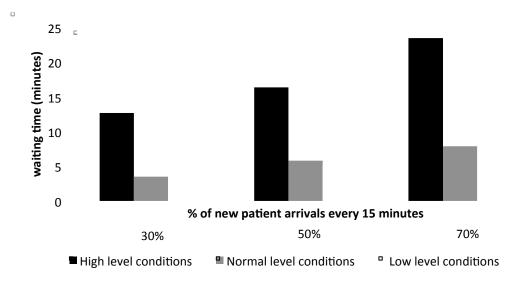


Figure 1: Patient waiting time for check-in under different new patient arrivals' scenarios.

The simulation study developed by Mocarzel et al. (2013) focused on the front desk operation of the clinic under consideration. The computational results showed that with a balanced schedule of new and existing patients throughout the day, the performance and quality of service of the clinic can be improved. Since it takes a longer time to check-in a new patient, having multiple new patients arriving at the same time increases the waiting times at the front desk. Also, the extra time involved in checking-in new patients would be an obstacle for answering calls. Figure 1 shows the results obtained for patient waiting times while considering three different patient arrival rates (high level, normal level, and low level) and three different percentages of new patient arrivals (30%, 50%, and 70%). For instance, a high level condition with 50% means that the clinic should expect a high volume of patients arriving every 15 minutes

(minimum appointment duration) from which 50% of the patients are classified as new patients. The graph shows an increasing trend of waiting time as the percentage of new patient arrivals increases because there is extra queuing.

Overall, keeping the percentage level of new patients arriving to the clinic every 15 minutes at or below 30% would decrease the work load on the staff, decrease the waiting time for patients to check-in, and relatively decrease the number of patients waiting in queue to check-in for their appointment. In the next sections, we addressed the question of how to balance the arrival of new and existing patients for every time period while considering the patient demand and the doctor's availability.

### 4 PATIENT SCHEDULING

This section turns to patient and resource scheduling and formulates an integer program to find the best appointment times for new patients. The IP is part of the framework that integrates with the current discrete-event simulation model for patient admission planning and the intermediate term allocation of resource capacities. The framework uses the simulation model to find the best balance of new and existing patients arriving to clinic at the beginning of each appointment period. The IP assigns specific time appointment slots to new patients during the day by solving the formulation using a "representative" historical demand and doctors' availability for each day of the week. The IP produces an optimal calendar schedule for the doctors, i.e. the best appointment time for each doctor to see new patients according to their availability. For convenience, we list the notation of the IP in Table 1.

Table 1: Scheduling problem sets, parameters and variables.

### **Indexes**

I: set of doctors indexed i

J: set of patient types, indexed j (j = 1 new patient, j = 2 existing patient)

T: set of 15 minute time slots, indexed t

L: set of appointment start times, indexed l

### **Parameters**

 $p_{ij}$ : number of patients of type j requesting an appointment with doctor i

 $n_t$ : number of new patients allowed at each time period t

### **Decision Variables**

 $x_{ijt}^l = 1$  if time period t is occupied by patient type j seeing doctor i, otherwise  $x_{ijt}^l = 0$ 

 $w_{ij}^l = 1$  if a patient type j has an appointment with doctor i starting at time period l, otherwise  $w_{ij}^l = 0$ 

We now state the model IP:

$$IP: Max z: \sum_{i \in I} \sum_{j \in J} \sum_{l \in L} w_{ij}^{l}$$
 (1)

subject to:

$$\sum_{l \in L} w_{ij}^l \le p_{ij} \quad , \forall i \in I, \quad \forall j \in J$$
 (2)

$$\sum_{i \in I} \sum_{l=t-1}^{t} x_{ijt}^{l} \le n_t \quad , \forall t \in T, \quad j = 1$$
(3)

$$\sum_{j \in I} \sum_{l=t-1}^{t} x_{ijt}^{l} \le 1 \qquad , \forall t \in T, \quad \forall i \in I$$
 (4)

Sowle, Gardini, Vazquez Arroyo Vazquez, Pérez, Jimenez, and DePagter

$$\begin{aligned} x_{ijt}^{l} - w_{ij}^{l} &= 0 &, \forall i \in I, \quad j = 1, \quad \forall t \in T, \quad l = \{t - 1, \ t\} \\ x_{ijt}^{l} - w_{ij}^{l} &= 0 &, \forall i \in I, \quad j = 2, \quad \forall t \in T, \quad l = t \\ x_{ijt}^{l} &\in \{0,1\} & w_{ij}^{l} &\in \{0,1\} &, \forall i \in I, \quad \forall j \in J, \quad \forall l \in L, \quad \forall t \in T \end{aligned}$$
 (5)

$$x_{ijt}^l - w_{ij}^l = 0 \qquad , \forall i \in I, \quad j = 2, \quad \forall t \in T, \quad l = t$$
 (6)

$$x_{ijt}^l \in \{0,1\}$$
  $w_{ij}^l \in \{0,1\}$  ,  $\forall i \in I, \forall j \in J, \forall l \in L, \forall t \in T$  (7)

The objective function (1) maximizes the number of appointments for the day. The decision variable  $x_{iit}^l$  is a binary variable that equals 1 if time period t is occupied by a patient type j seeing doctor i. Likewise, the decision variable  $w_{ij}^l$  equals 1 if a patient type j has an appointment with doctor i starting at time period l. Variables  $x_{ijt}^l$  and  $w_{ij}^l$  are related through constraints (5) and (6) and together they control the patient volume. Constraint (2) forces the model to schedule at most  $p_{ij}$  patients of type j for each doctor i. Constraint (3) checks that at most  $n_t$  new patients are scheduled per appointment time period. Constraint (4) ensures that at most one patient is scheduled for each doctor per time period. Constraints (5) and (6) are used to reserve sequential time periods for those appointments requiring more than one 15 minute time slot.

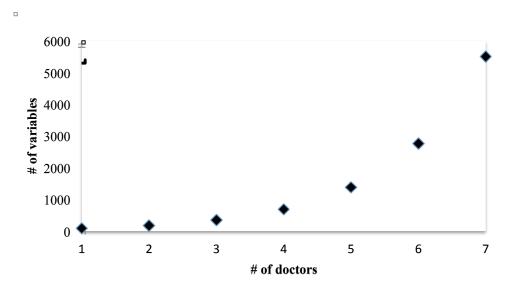


Figure 2: IP number of variables as the number of doctors increase.

For instance, some appointments will require two 15 minute appointment time periods to be completed. The model makes sure that new patients occupy two time periods. Constraint (7) requires each variable to be binary. The IP model is NP-Hard and difficult to solve. As the number of doctors increases in the model, there is an exponential increase in the amount of variables. Figure 2 shows the increasing trend. For example, if the number of doctors increases from four to five, then the number of variables increases from 688 up to 1376. Although the problems is NP-Hard, it can be solved with Microsoft Excel using the open source OpenSolver (www.opensolver.org) Add-in. In most cases the solution is found in less than 30 seconds.

#### 5 APPLICATION

To test and validate our methodology, we applied it to the Live Oak Health Partners clinic, a multispecialty medical practice located in San Marcos, Texas. The patient scheduling model was implemented in Microsoft Excel and tested using the clinic simulation model by Mocarzel et al. (2013). The key assumptions of the simulation model include Poisson patient arrivals to the clinic, which is based on historical data, and patient type and doctor requested, which are based on empirical distributions. In the next subsection we describe the configuration of the clinic and, in Section 5.2, we present our experiment setup. We report computational results and findings in Section 5.3.

### 5.1 Real multi-specialty outpatient clinic setting

Live Oak Health Partners is a Texan medical practice with locations in San Marcos, Kyle, Lockhart and Wimberley. Our work focuses on the San Marcos location, where the clinic operates nine hours a day, five days a week, and it is not open during weekends. The clinic has seven doctors with four different specialties: orthopedics, surgery, ENT, and audiology. Table 2 lists the names of the doctors and their availability to see patients during the week. Each doctor has a preference in terms of the time duration for their appointment. Most of the doctors allocate 15 minute appointments for existing patients and 30 minute appointments for new patients. The consultation with a new patient requires more time the physician spends the majority of the time getting familiar with the patient's health record. Table 3 lists the appointment duration times for each doctor at the clinic. This information is very important when formulating the IP discussed in Section 4.

Name	Specialty	Monday	Tuesday	Wednesday	Thursday	Friday
Doctor 1	Orthopedics	8am-12pm 1:30pm-5pm		8am-12pm 1:30pm-5pm		8am-12pm 1:30pm-4pm
Doctor 2	Orthopedics		8am-12pm 1:30pm-5pm	8am-12pm	8am-12pm 1:30pm-5pm	
Doctor 3	ENT	8am-12pm 1:30pm-5pm	8am-12pm 1:30pm-5pm	8am-12pm 1:30pm-5pm		8am-12pm
Doctor 4	Surgeon		9am-10:45am 1:30pm-5pm		9am-11am	
Doctor 5	Surgeon	8am-12pm		1:30pm-5pm	1pm-5pm	8am-12pm
Doctor 6	Surgeon	1pm-5pm		8am-12pm	8am-12pm	8am-12pm
Doctor 7	Audiologist	8am-12pm 1pm-5pm	8am-12pm 1pm-5pm	8am-12pm 1pm-5pm	8am-12pm 1pm-5pm	8am-12pm 1pm-5pm

Table 2: Weekly schedule for physicians.

Table 3: Appointment durations for new and existing patients.

Name	Specialty	Existing	New
Doctor 1	Orthopedics	15 min	15min
Doctor 2	Orthopedics	15min	30min
Doctor 3	ENT	15 min	30min
Doctor 4	Surgeon	15 min	30min
Doctor 5	Surgeon	15 min	30min
Doctor 6	Surgeon	15min	30min
Doctor 7	Audiologist	15-30min(depend rea-	30-60 min(depends rea-
		son for visit)	son for visit)

# 5.2 Experimental Setup

The clinic configuration used for testing and validating our methodology is based on the resources/doctors listed in Table 2, the appointment durations listed in Table 3, and the historical patient demand data for one month, which was provided by the clinic. The clinic serves an average of 73 patients

per day. The expected number of patients to schedule for each doctor per day of the week was computed using the historical data and the results are showed in Table 4. In Table 4, letters "E" and "N" stands for existing and new patients respectively.

Day of the	Doc	tor 1	Doctor 2		Doctor 2		tor 2 Doctor 3		Doctor 7		Doctor 4		Doctor 6		Doctor 5	
week	E	N	E	N	E	N	E	N	E	N	E	N	E	N		
Monday	14	11			16	9	2	3			6	5	12	8		
Tuesday			12	6	16	10	3	1	2	1						
Wednesday	16	12	1	1	17	6	4	0			6	2	11	2		
Thursday			20	9			5	1	5	0	3	1	10	4		
Friday	7	4			7	8	2	0			1	1	5	0		

Table 4: Average patient demand per day for each doctor.

The computational study will test three different balancing strategies for scheduling new and existing patients for each day of the week. We will consider the three scenarios discussed in Section 3, where the percentage (%) of new patients per time period is constrained to be 30%, 50%, and 70%. The results will provide guidelines on when to schedule new patients according to the doctor's availability, the day of the week, and the percentage (%) of new patients to be served per time period. Since the clinic has seven doctors, we assume that the maximum number of patients arriving per time period is seven when all doctors are available. Therefore, the number of new patients allowed to be scheduled per time period  $(n_t)$  can be computed as follows:

 $n_t = [number\ of\ doctors\ at\ the\ clinic \times \%\ of\ new\ patients\ per\ time\ period]$ 

Notice that  $n_t$  is one of the parameters of constraint (3) of the IP model. Due to space limitations in the document, we consider only one the day of the week in our computational study, Monday. Since only five doctors are available on Mondays the experimental set-up the computational study as described in Table 5.

Experiment	%	# of new patients per time period
1	30	1
2	50	2
3	70	3

Table 5: Number of new patients allowed to be scheduled per time period.

## 5.3 Computational Results

We now report computational results to evaluate the schedules provided by the IP model for the three experiments discussed in Section 5.2. Due to space limitations, we report and discuss the results for only one of the day of the week, Monday. Monday was selected because is one of the days with higher demand. However, only five of the seven doctors are available on Monday as reported in Table 2. Next, we present the schedules for Monday based on the expected demand for that day and provide some recommendations for the clinic operations.

Figure 3 depicts the optimal schedule for the expected demand reported for Mondays (see Table 4) when only 30% of the patients arriving at each time period are of type new. The solution of the IP model

provided appointments for most of the patients, but not for all of them. A total of 74 patients were scheduled out of the 86 expected for the day. Since in this first experiment the maximum number of new patients allowed per time period equals one, some of the new patients for the day are left out of the schedule. For instance, out of the 9 new patients expected for Doctor 3 only 4 were scheduled. Similarly, none of the new patients expected for Doctor 7 were scheduled. All of the patients for Doctor 1 were accommodated in the schedule for the day. Doctor 1 is the only doctor in the clinic that has 15 minute appointments for both new and existing patients; therefore, he can accommodate more patients into his daily schedule when compared to the other doctors. The IP model accommodates most of the new patients for Doctor 3 in the morning. Most of Doctor 3 new patient's appointments do not overlap with Doctor 1 new patients appointments since the model avoid the overlapping of new patients arriving at the same appointment time. Doctor 5' appointments were scheduled in the morning because he is not available in the afternoon. In contrast, Doctor 6 had all his appointments scheduled in the afternoon because he is not available in the morning.

Figures 4 and 5 depict the optimal schedule when 50% and 70% of the patients arriving at each time period are new, respectively. In Figure 4, the optimal schedule allows for a maximum of two new patients per time period and in Figure 5 the optimal schedule allows for a maximum of three new patients per time period. In both cases, the IP model solution provided a schedule where all the expected patients were accommodated. A total of 86 patients were accommodated for the day. Most of Doctor 1's new patients were scheduled in the morning. The morning schedule for Doctor 1 has two one hour blocks for accommodating existing patients and one 90 minute block for accommodating new patients. In the afternoon, Doctor 1 has two small 30 minute blocks for new patients and the rest of the time is reserved for existing patients. The solution for Doctor 3 accommodated existing patients at the beginning and at the end of the morning schedule and pushed most of the new patients to the afternoon where a block of 150 minutes is reserved for new patients. For the rest of the doctors, there is no specific structure to accommodate patients into the schedule. Schedule blocks for new and existing patients are only observed for doctors expecting a high number of patients, which is the case for Doctor 1 and Doctor 3. The rest of the doctors schedules are manipulated around the blocks for those two doctors expecting a high number of patients. Finally, it is observed that no change in the schedule happened when increasing the percentage of new patients arriving at each time period from 50% to 70%, Figures 4 and 5 respectively.

	1															
									Morni	ng						
Doctor	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45
Doctor 1	N	Е	Е	Е	Е	N	Е	Е	N	E	E	Е	Е	N	N	N
Doctor 2																
Doctor 3		Е		1	1	Е	1	7		1	1	Е	Е			
Doctor 4																
Doctor 5	Е	1	N		Е	Е	Е	Е	Е		Е	1	1			Е
Doctor 6																
Doctor 7	1	E									I	3			I	E
									Afterno	oon						
Doctor	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45
Doctor 1			Е	Е	N	N	N	N	Е	Е	Е	E	E	Е	N	N
Doctor 2																
Doctor 3				Е	Е		Е		1	1	Е	Е	Е	Е	Е	
Doctor 4																
Doctor 5																
Doctor 6	1	N	1	N		Е	Е	Е	Е		1	1	1	N	Е	Е
Doctor 7			]	E		]	Е		Е		1	Ξ			I	Е

Figure 3: Monday schedule with only 30% new patients allowed per time period.

Sowle, Gardini, Vazquez Arroyo Vazquez, Pérez, Jimenez, and DePagter

	Morning															
Doctor	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45
Doctor 1	N	Е	Е	Е	Е	N	N	N	N	N	N	Е	Е	Е	Е	N
Doctor 2																
Doctor 3	Е	Е	Е	1	7	Е	1	1	N	1	1	1	Е	Е	Е	Е
Doctor 4																
Doctor 5	Е	1	1	E	1	1	Е	Е	E	E	E	1	N	1	1	Е
Doctor 6																
Doctor 7	N E E E E N															
								_	_	_		_				
		-							Afterno							
Doctor	1:00			1:45	2:00	2:15	2:30				3:30	3:45	4:00	4:15	4:30	4:45
	1:00			1:45 E					Afterno	oon			4:00 E	4:15 E		4:45 N
Doctor	1:00		1:30		2:00	2:15	2:30	2:45	Afterno	3:15	3:30	3:45			4:30	
Doctor Doctor 1	1:00		1:30		2:00	2:15 N	2:30	2:45 E	Afterno	3:15 E	3:30	3:45 E		Е	4:30	
Doctor Doctor 1 Doctor 2	1:00		1:30 E	Е	2:00 N	2:15 N	2:30 E	2:45 E	Afterno 3:00 E	3:15 E	3:30 E	3:45 E	Е	Е	4:30 N	N
Doctor Doctor 1 Doctor 2 Doctor 3	1:00		1:30 E	Е	2:00 N	2:15 N	2:30 E	2:45 E	Afterno 3:00 E	3:15 E	3:30 E	3:45 E	Е	Е	4:30 N	N
Doctor 1 Doctor 2 Doctor 3 Doctor 4	1:00	1:15	1:30 E	E	2:00 N	2:15 N	2:30 E	2:45 E	Afterno 3:00 E	3:15 E	3:30 E	3:45 E	Е	E	4:30 N	N E

Figure 4: Monday schedule with only 50% new patients allowed per time period

In terms of the operation of the clinic front desk, we observed that the clinic can accommodate more patients when two new patients are allowed to be scheduled per time period. However, based on the results discussed in Section 3, if we want to minimize the waiting time at the front desk we should limit the number of new patients arriving per time period to one. Recall that new patients take more time for check-in at the front desk. Therefore, there is a trade-off between the number of patients that can be scheduled at the clinic versus the patient waiting time at the front desk and it is up to the clinic to make a decision. In addition, there might be alternative optimal schedules for the daily operation of the clinic.

	Morning															
Doctor	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45
Doctor 1	N	Е	Е	Е	Е	N	N	N	N	N	N	Е	Е	Е	Е	N
Doctor 2																
Doctor 3	Е	Е	Е	1	N	Е	1	1	1	1	1	1	Е	Е	Е	Е
Doctor 4																
Doctor 5	Е	1	7	Е	1	7	Е	Е	Е	Е	Е	1	V	1	7	Е
Doctor 6																
Doctor 7		1	1		I	Ε	]	Ε	]	Ε	]	Ξ		1	1	
									Afterno	oon						
Doctor	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45
Doctor 1			Е	Е	N	N	Е	Е	E	E	Е	Е	Е	Е	N	N
Doctor 2																
Doctor 3			Е	Е	1	1	1	1	1	1	1	1	1	N	Е	Е
Doctor 4																
Doctor 5																
Doctor 6	1	1	1	1	Е	Е	Е	Е	Е	Е	1	V	1	N	1	1
Doctor 7		1	1		I	Е			N		]	Ξ	]	Е	I	Ξ

Figure 5: Monday schedule with only 70% new patients allowed per time period

### 6 DISCUSSION AND CONCLUSIONS

This paper presents the results of an ongoing effort to develop an integrated framework targeting the patient admission planning and the intermediate-term allocation of resource capacities for a multi-specialty outpatient clinic located in San Marcos, TX. The critical need is to concurrently improve key performance indicators such as: a) reducing the patient's wait time prior to seeing a doctor and b) reducing the number of phone calls that are unanswered by the clinic's staff members. In the first part of this project, a discrete event simulation model, developed in Arena, was used for conducting an analysis of variance (ANOVA) on factors such as number of staff members, number of phone calls received, number of patient arrivals, percentage of phone calls requesting new appointments. The study recommends a balance in the schedule of the two different patient types (new and existing) to decrease the patient's checked-in waiting time at the front desk.

This paper builds upon the recommendations provided by Mocarzel *et al.* (2013) and develops an integer programming model that balances the number of existing and new patients to be scheduled at the clinic for each appointment time period. A case study was presented to provide an optimal schedule for five doctors during a one-business-day time horizon. The results showed that, when only one new patient is allowed to be scheduled at each 15-minute appointment period, the model was not capable of scheduling all the expected new patient requests. However, if the number of new patients allowed to be schedule at each 15-minute appointment period is greater or equal to two, the model is capable of scheduling all the expected new patient requests. Based on the results discussed in Section 3, if the clinic manager wants to minimize the waiting time at the front desk for the case study, the number of new patients arriving per time period should be limited to one. Recall that new patients take more time for check-in at the front desk. Therefore, based on the results of this research, there is a trade-off between the maximum number of patients that can be scheduled at the clinic versus the patient waiting time at the front desk. For instance, in the case study, limiting the number of new patients allowed to be schedule at each 15-minute appointment period to one, minimizes the patient waiting time but reduces the number of patients that can be scheduled for the day at the clinic.

As part of our future work, we would like to integrate the scheduling module with the discrete event simulation module. The idea is to test the front-desk performance provided an optimal schedule is generated for the number of appointment requested for a given day. Furthermore, the simulation will allow us to evaluate the schedule given that the system is subject to stochastic factors, such as late patient arrivals and doctor-patient consultation extends over the 15-minute period.

### **ACKNOWLEDGEMENTS**

The authors would like to thank the staff of the Live Oak Health Clinic in San Marcos for their help in the data collection phase of the project. In particular we would like to recognize Yesenia Castillo for their assistance and feedback. We would like to thank Dr. Tongdan Jin for the support provided in the development of the optimization model and in the analysis of the results.

### REFERENCES

- Cayirli, T., E. Veral, and H. Rosen. 2006. "Designing Appointment Scheduling Systems for Ambulatory Care Services." *Health Care Management Science*, 9: 47-58.
- Gul, S., B. T. Denton, J. Fowler, and T. Huschka. 2011. "Bi-Criteria Scheduling of Surgical Services for an Outpatient Procedure Center." *Production and Operations Management*, 20(3): 406-417.
- Gupta, D., and B. Denton. 2008. "Appointment Scheduling in Health Care: Challenges and Opportunities." *IIE Transactions*, 40(9): 800-819.

- Ho, C.J., and H.S. Lau. 1992. "Minimizing Total Cost in Scheduling Outpatient Appointments." Management Science, 38(12): 1750-1764.
- Ho, C.J., H.S. Lau, and J. Li. 1995. "Introducing Variable-Interval Appointment Scheduling Rules in Service Systems." *International Journal of Production & Operations Management*, 15(6): 59-69.
- LaGanga, L.R., and Lawrence, S.R. 2007. "Clinic Overbooking to Improve Patient Access and Increase Provider Productivity." *Decision Sciences*, 38(2): 251-276.
- Liu, L, and X. Liu. 1998a. "Block Appointment Systems for Outpatient Clinics with Multiple Doctors." Journal of the Operations Research Society, 49: 1254-1259.
- Liu, L , X. Liu. 1998b. "Dynamic and Static Job Allocation for Multi-Server Systems." *IIE Transactions*, 30: 845-854.
- Mocarzel, B., S. David, U. Berkcan, E. Pérez, J. Jimenez, and L. DePagter. 2013. "Modeling and Simulation of Patient Admission Services in a Multi-Specialty Outpatient Clinic." *In Proceedings of the 2013 Winter Simulation Conference* edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M.E. Kuhl,, pp. 2309-2319. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
- Pérez, E., L. Ntaimo, C. Bailey, and P. McCormack. 2010. "Modeling and Simulation of Nuclear Medicine Patient Service Management in DEVS. *Simulation*, 86(8-9): 481-501.
- Pérez, E., L. Ntaimo, W.E. Wilhelm, C. Bailey, and P. McCormack. 2011. "Patient and Resource Scheduling of Multi-Step Medical Procedures in Nuclear Medicine." *IIE Transactions on Healthcare Systems Engineering*, 1(3): 168-184.
- Pérez, E., L. Ntaimo, C. Malavé, C. Bailey, and P. McCormack. 2013. "Stochastic Online Appointment Scheduling of Multi-Step Sequential Procedures in Nuclear Medicine." *Health Care Management Science*, 16(4): 281-299.
- Robinson, L.W., and R.R. Chen, R.R. 2003. "Scheduling Doctors' Appointments: Optimal and Empirically-Based Heuristic Policies." *IIE Transactions*, 35(3): 295-307.

### **AUTHOR BIOGRAPHIES**

**TRAVIS SOWLE** is an undergraduate student at Texas State University, Ingram School of Engineering, pursing a degree in Industrial Engineering with a minor in Mathematics. He is expected to graduate from Texas State in December 2014. He is the acting group leader of the project.

**NATALIE GARDINI** is an undergraduate student at Texas State University, Ingram School of Engineering, pursuing a degree in Industrial Engineering. She is expected to graduate from Texas State University in May 2015.

**FERNANDO VAZQUEZ ARROYO VAZQUEZ** is an undergraduate student at Texas State University, Ingram School of Engineering, pursing a degree in Industrial Engineering with a minor in Mathematics. He is expected to graduate from Texas State in December 2014.

**EDUARDO PEREZ** is an Assistant Professor at Texas State University, Ingram School of Engineering, San Marcos, Texas, USA. He obtained his B.S. in Industrial Engineering from the University of Puerto Rico, Mayagüez Campus and his Ph.D. in Industrial Engineering from Texas A&M University. His research interests include healthcare systems engineering and analysis, patient and resource scheduling, and optimization and simulation techniques. He is a member of INFORMS, IIE, and Tau Beta Phi. His email address is eduardopr@txstate.edu.

**JESUS A. JIMENEZ** is an Associate Professor in the Ingram School of Engineering at Texas State University. He received his B.S. and M.S. in Industrial Engineering from The University of Texas at El Paso, and his Ph.D. in Industrial Engineering from Arizona State University. His research interests are in simulation modeling and analysis of manufacturing systems; discrete-event and agent-based simulation; design of simulation experiments; and sustainable lean manufacturing. He is member of INFORMS and IIE. His email address is jesus.jimenez@txstate.edu.

**LENORE DEPAGTER** is Physician Practice Administrator of Live Oak Health Partners. She obtained a degree of Doctor of Osteopathy from the University of North Texas Health Science Center- Fort Worth and completed a combined residency in Internal Medicine and Pediatrics at Scott & White Memorial Hospital. She is a current MBA candidate at the University of Texas at Dallas/Southwestern Medical Center. She is an alumni of Texas State University.