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TOWARDS A SIMULATION BASED METHODOLOGY FOR SCHEDULING PATIENT AND PROVIDERS AT OUTPATIENT CLINICS

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ABSTRACT

In this paper we develop a simulation based methodology for planning the schedules of providers and the appointment for patients. The methodology combines discrete-event simulation and optimization. Two types of patients are considered in this study: new and existing. In addition patient no-shows and walk-ins are also considered. 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. We report on computational results based on a real clinic, historical data, and both patient and management performance measures.

1 INTRODUCTION

In multispecialty outpatient clinics patients who want to be seen by a doctor make appointments by telephone and are scheduled with the doctor that specializes in their specific ailment. In addition to scheduled patients, some patients decide to visit the clinic without an appointment which is commonly known as a walk-in. When patients comes in for service they go through the check-in process where they fill out paperwork while a staff member verifies their insurance. The volume of documentation that a patient is required to submit at the time of check-in varies. A patient visiting the clinic for the first time is considered a new patient and is required to complete more paperwork than those already in the system. New patients also require more attention from the front desk staff which limits the staff capability to do other things and create queues in the system. After the patient is checked-in, they wait in the waiting room until a nurse calls them back to be serviced by the doctor. After seeing the doctor, the patient goes back to the front desk to check-out. In general, patients expect short waiting times and service times when coming to the clinic to receive service; otherwise, there will patient dissatisfaction which impact the quality of service perceived by the patient.

Patient waiting time and quality of service is a topic that have generated a lot of interest from the research community. There is extensive literature in topics related to reducing patient waiting times, patient scheduling, and resource management in healthcare. Still, there is a need for research that consider the impact of the clinics front desk operation in the quality of service perceived by the patient. Most of the time clinics are modeled as a single server where the server is the provider. Since providers are only available on specific days and times during the day is important to manage the clinic front desk efficiently to achieve the best utilization of these resources.

This work builds upon the work by (Mocarzel et al. 2013) and (Sowle et al. 2014). In the first paper a discrete-event simulation model was develop to study the front desk operation of an outpatient clinic. The simulation model captured the processes occurring at front desk including answering phone calls, patient check-in and check-out, and documentation. The computational study concluded that patient waiting time can be reduced by creating balanced schedule of new and existing patients arriving at each appointment time. However, the authors did not provided guidelines to schedule patients in a balanced way. (Sowle et al. 2014) developed an integer programming (IP) model for patient admission planning and the allocation of providers that considered new and existing patients. In this paper we extend the IP model described in (Sowle et al. 2014) by consider patient walk-ins and no-shows. The new IP provides appointment allocation policies for doctors during the day, i.e. the best appointment time to be reserved to patient walk-ins or for new patients so that congestion at the clinic front desk is minimized.

The rest of the paper is organized as follows. In section 2 we review some papers related to this work. The problem is described in detail in Section 3. Section 4 includes the new IP model and Section 5 provides a discussion of the computational study performed using the new IP. We end the paper in Section 5 with our conclusions and future work.

2 LITERATURE REVIEW

Healthcare clinics are always searching for means to optimize their services while lowering cost. Of the most valuable measurements for quality of service, the patient waiting time is of highest importance for it increases customer satisfaction. There are multiple sources of literature that educates how operations research techniques can be utilized to model and improve service operations and patient flow in healthcare. More importantly, simulation and mathematical models are reliable tools when comprehending and optimize these systems. For instance, (Ho and Lau 1992) and (Ho et al. 1995) examined several appointment guidelines within different healthcare clinic settings They concluded that no set guideline was capable of improving all the performance measures for every clinic setting. Therefore, a heuristic approach was introduced to decide a guideline depending on the distinctive nature of each setting.

(Liu and Liu 1998a) and (Liu and Liu 1998b) determined 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 analyze the system under different appointment guidelines. The model benefited the optimization of the scheduling times when a specific sequence of patients was followed. (Cayirli et al. 2006) realized that differing appointment rules do not have as much of an effect on optimality as to patient sequencing which was concluded by observing 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. (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.

In this research, the goal is to reduce the waiting time at the clinic by balancing the number of new patients arriving at the same time for their check-in taking into consideration walk-ins and no shows. Also, a multispecialty clinic is considered with multiple doctors with independent schedules and preferences in terms of appointment durations and how such parameters affect the optimization. This is a highly constrained healthcare setting and the scheduling of patients in such an environment was determined 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 with their availability depending on each day of the week. For instance, some of the doctors may be scheduled three days of the week while others are available only during half of a work day. Schedule appointments for all doctors are managed by a centralized front desk with four staff members accepting calls throughout the day. 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 in hand at the clinic are patient complaints about difficulty connecting to anyone on the phone to schedule their appointments as well as extended waiting times to check-in and check-out of the clinic.

A discrete event simulation model was developed to represent the operations at the front desk of the clinic. The model consider four staff members each performing a some of the tasks mentioned above. The simulation consider two types of patients existing and new. Existing patients are patients that are already on the systems and new patients are those patients visiting the clinic for the first time. The performance measurement considered include the waiting time for check-in and check-out, the patient waiting time on the phone when requesting an appointment, the number of unanswered calls, the number of patients waiting in queue, and the front desk staff utilization. The model was built using SIMAN Arena.

The computational results by the simulation study developed by (Mocarzel et al. 2013) focusing on front desk operations 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. Knowing it takes more time to check-in a new patient, having multiple new patients arriving at the same time increases the waiting times at the front desk as well as complicating the answering of calls. Figure 1 demonstrates the results for patient waiting times while taking into consideration three different patient arrival rates at high level, normal level, and low level with three different percentages of new patient arrivals: 30%, 50%, and 70%. As the percentage of new patients increases in a deterministic arrival rate of 15 minutes, the waiting time increases for all conditions.

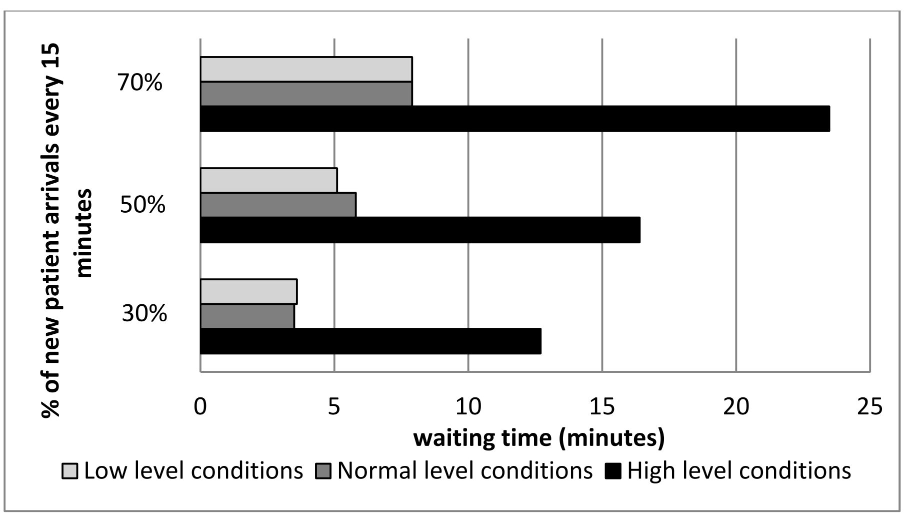

Figure 1: Patient waiting time for check-in under different new patient arrivals’ scenarios.

4 PATIENT SCHEDULING

In this section we formulate our new IP model for scheduling new and existing patients to providers while considering patient walk-ins and no-shows. The notation for the model is described in Table 1. The IP model uses the output of the simulation model, in terms of the best balance of new and existing patients, as an input for parameter n_t. The IP assigns specific time appointment slots to patients using an expected demand and providers availability during the week. The IP model provides an optimal policy for appointment assignment based on the expected demand, i.e. the best appointment times to take care of new patients, to double book, and to serve existing patients.

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}: expected number of patients of type j requesting an appointment with doctor i q_{ij}: expected number of patients walk-ins of type j requesting an appointment with doctor i r_{ij}: expected number of no-shows of type j for 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 $x_{ijt}^l = 0$ y_{ijt}^l = 1 if time period t is reserved for a patient walk-in of type j to see doctor i, otherwise $y_{ijt}^l = 0$ 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 u_{ij}^l = 1 if a patient no-show of type j is expected for doctor i at time period l , otherwise u_{ij}^l = 0 v_{ij}^l = 1 if a patient walk-in of type j has an appointment with doctor i starting at time period l , otherwise v_{ij}^l = 0

We now state the model IP:

$$\textbf{\textit{IP}} : Max\ z\text{: } \textstyle\sum_{i\in I}\sum_{j\in J}\sum_{l\in L}(w_{ij}^l + v_{ij}^l) \qquad (1)$$

subject to:

$$\textstyle\sum_{l\in L} w_{ij}^l \le p_{ij},\ \sum_{l\in L} v_{ij}^l \le r_{ij},\ \sum_{l\in L} u_{ij}^l \le q_{ij}, \forall i \in I, \quad \forall j \in J \qquad (2)$$

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

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

$$x_{ijt}^l - w_{ij}^l = 0 \qquad ,\forall i \in I, \quad j = 1, \quad \forall t \in T, \quad l = \{t-1,\ \ t\} \qquad (5)$$

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

$$y_{ijt}^l - v_{ij}^l = 0 \qquad ,\forall i \in I, \quad j = 1, \quad \forall t \in T, \quad l = \{t-1,\ \ t\} \qquad (7)$$

$$y_{ijt}^{l} - v_{ij}^{l} = 0 \qquad , \forall i \in I, \quad j = 2, \quad \forall t \in T, \quad l = t \tag{8}$$

$$x_{ijt}^{l} \in \{0,1\},\ w_{ij}^{l} \in \{0,1\},\ y_{ijt}^{l} \in \{0,1\},\ u_{ij}^{l} \in \{0,1\}, v_{ij}^{l} \in \{0,1\}, \forall i \in I, \quad \forall j \in J, \quad \forall l \in L, \quad \forall t \in T \tag{9}$$

The objective function (1) maximizes the number of patients to serve during the day including patient appointments and walk-ins. Constraints (2) forces the model to schedule at most p_{ij} patients and r_{ij} walk-ins of type j for each provider i. Constraint (3) forces the model to schedule at most n_t new patients per time period. Constraint (4) is used to make sure that only one patient is assigned to each provider per time period. Constraints (5) to (8) are used to reserved sequential time periods for new patients that require 30 minutes appointments. Constraint (9) requires each variable to be binary. The IP problem was solved with Microsoft Excel using the Open Solver (www.opensolver.org) Add-in.

5 APPLICATION

We applied our methodology to the Live Oak Health Partners clinic located in San Marcos, Texas. The clinic has seven providers with four different specialties: orthopedics, surgery, ENT, and audiology. Table 2 shows the providers availability during the morning for each day of the week. Each doctor decides the amount of time to be allocated to their appointment and most of them allocate 15 minutes to existing patients and 30 minutes to new patients. Table 3 list the appointment time duration for each doctor. This information is important for formulating the IP problem discussed in Section 4.

Table 2: Weekly morning schedule for physicians.

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

Table 3: Appointment durations for new and existing patients.

Name	Specialty	Existing		New	
		15 min	30 min	15min	30 min
Doctor 1	Orthopedics	x		x	
Doctor 2	Orthopedics	x			x
Doctor 3	ENT	x			x
Doctor 4	Surgeon	x			x
Doctor 5	Surgeon	x			x
Doctor 6	Surgeon	x			x
Doctor 7	Audiologist	x			x

5.1 Experimental Setup

The historical patient demand data for one month was used to compute the expected number of patients per day at the clinic which are listed in Table 4. In Table 4, letters “E”, “N”, “WI”, and “NS” stand for existing, new, walk-in and no-show patients respectively.

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

Name	Patient Type	Monday	Tuesday	Wednesday	Thursday	Friday
Doctor 1	E	8		9		4
	N	7		7		2
	WI	E=0, N=2		E=1, N=1		E=0, N=0
	NS	E=0, N=0		E=0 , N=0		E=0, N=0
Doctor 2	E		7	5	10	
	N		3	3	5	
	WI		E=1, N=0	E=1, N=0	E=1, N=1	
	NS		E=1, N=0	E=1, N=0	E=3, N=1	
Doctor 3	E	10	9	8		4
	N	4	5	4		4
	WI	E=1, N=1	E=1, N=1	E=0, N=1		E=0, N=0
	NS	E= 3, N=0	E=0, N=0	E=2, N=0		E=0, N=0
Doctor 4	E		2		3	
	N		1		0	
Doctor 5	E	7				5
	N	4				2
Doctor 6	E			3	3	1
	N			2	2	1
Doctor 7	E	2	3	2	3	2
	N	3	1	0	1	0

The computational study considered three different balancing strategies for scheduling new and existing patients for each day of the week. The three scenarios discussed in Section 3 were considered, where the percentage (%) of new patients per time period is constrained to be 30%, 50%, and 70%. The results obtained will provide insights 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:

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

For instance, since only four doctors are available on Monday mornings the experiments are set up as listed in Table 5.

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

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

5.2 Computational Results

We now report computational results to evaluate the schedules provided by the IP model for the three experiments consisting of changing the number of new patients that are allowed during a time period from 1, 2, and 3 for each day of the workweek. Due to space limitation we only report the results for Monday mornings. Monday was selected because is the day of the week with the highest patient demand. Only four of the seven doctors are available on Monday mornings as reported in Table 2. Next we present the computational results based on the expected demand for Monday mornings and provide insights based on these results.

Figure 3 depicts the optimal schedule for Monday. 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. Having only one new patient per time period decreases the amount of patients that can be scheduled within a 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 seven new patients that demand an appointment for Doctor 1 only six were scheduled. The same problem happens with Doctors 3 and 5 both being two new patients short. Doctor 3 was also schedules one less existing patient than demanded. Dropping the total patients scheduled to only thirty-nine out of forty-five showing six patients were missed. The model schedules two existing patients in the same time period because they are expecting three no shows for Doctor 3 on Monday. The model schedules an extra patient to make up for the patient that will not show up to their appointment. Doctor 3 has a demand of three no shows, but also has a demand of two walk ins so the model doesn't apply all three no shows.

	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	Total	N	E
Doctor 1	E	E	E	E	E	E	E	E	N	N		N	N	N	N		14	6	8
Doctor 2																			
Doctor 3		N		E		2E	N			E	E	E	E	E	2E		11	2	9
Doctor 4																			
Doctor 5	E		E		E	N		N		E	E			E		E	9	2	7
Doctor 6																			
Doctor 7	N		N		N								E			E	5	3	2

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

Figure 4 and 5 depicts the results for when two or three new patients are allowed per time period respectively. For both cases the number of patients scheduled increases to forty-three out of forty-five patients and in both cases the maximum number of new patients starting their appointment in the same time period is two. Since the objective function of the scheduling model is to maximize the total number of patients scheduled for a day, and with only four doctors, allowing a third new patient to start at the same time will decrease the total number of patient scheduled. Recall that new patients use twice time for their appointments.

During both of these experiments doctors 5 and 7 met their demand of both new and existing patients. Doctors 1 and 3 both were short scheduling 1 new patient. Having two or three new patients per time period on a Monday allows to accommodate more patient into the schedule. However, based on the results discussed in Section 3, if the goal is to minimize the waiting time and queues at the front desk we should limit the number of new patient arrivals per appointment period to a minimum. 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.

<table>
<tr><th rowspan="2">Doctor</th><th colspan="16">Morning</th><th rowspan="2">Total</th><th rowspan="2">N</th><th rowspan="2">E</th></tr>
<tr><th>8:00</th><th>8:15</th><th>8:30</th><th>8:45</th><th>9:00</th><th>9:15</th><th>9:30</th><th>9:45</th><th>10:00</th><th>10:15</th><th>10:30</th><th>10:45</th><th>11:00</th><th>11:15</th><th>11:30</th><th>11:45</th></tr>
<tr><td>Doctor 1</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>N</td><td>N</td><td></td><td>N</td><td>N</td><td>N</td><td>N</td><td></td><td>14</td><td>6</td><td>8</td></tr>
<tr><td>Doctor 2</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 3</td><td></td><td>E</td><td></td><td>E</td><td>E</td><td>2E</td><td colspan="2">N</td><td colspan="2">N</td><td>E</td><td colspan="2">N</td><td>E</td><td>2E</td><td>E</td><td>13</td><td>3</td><td>10</td></tr>
<tr><td>Doctor 4</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 5</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td colspan="2">N</td><td colspan="2">N</td><td colspan="2">N</td><td>E</td><td></td><td>E</td><td colspan="2">N</td><td>11</td><td>4</td><td>7</td></tr>
<tr><td>Doctor 6</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 7</td><td colspan="2">N</td><td colspan="2">N</td><td></td><td colspan="2">N</td><td></td><td></td><td></td><td></td><td></td><td>E</td><td></td><td></td><td>E</td><td>5</td><td>3</td><td>2</td></tr>
</table>

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

<table>
<tr><th rowspan="2">Doctor</th><th colspan="16">Morning</th><th rowspan="2">Total</th><th rowspan="2">N</th><th rowspan="2">E</th></tr>
<tr><th>8:00</th><th>8:15</th><th>8:30</th><th>8:45</th><th>9:00</th><th>9:15</th><th>9:30</th><th>9:45</th><th>10:00</th><th>10:15</th><th>10:30</th><th>10:45</th><th>11:00</th><th>11:15</th><th>11:30</th><th>11:45</th></tr>
<tr><td>Doctor 1</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td>N</td><td>N</td><td></td><td>N</td><td>N</td><td>N</td><td>N</td><td></td><td>14</td><td>6</td><td>8</td></tr>
<tr><td>Doctor 2</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 3</td><td></td><td>E</td><td></td><td>E</td><td>E</td><td>2E</td><td colspan="2">N</td><td colspan="2">N</td><td>E</td><td colspan="2">N</td><td>E</td><td>2E</td><td>E</td><td>13</td><td>3</td><td>10</td></tr>
<tr><td>Doctor 4</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 5</td><td>E</td><td>E</td><td>E</td><td>E</td><td>E</td><td colspan="2">N</td><td colspan="2">N</td><td colspan="2">N</td><td colspan="2">N</td><td>E</td><td></td><td>E</td><td>11</td><td>4</td><td>7</td></tr>
<tr><td>Doctor 6</td><td colspan="16"></td><td></td><td></td><td></td></tr>
<tr><td>Doctor 7</td><td colspan="2">N</td><td colspan="2">N</td><td></td><td colspan="2">N</td><td></td><td></td><td></td><td></td><td></td><td>E</td><td></td><td></td><td>E</td><td>5</td><td>3</td><td>2</td></tr>
</table>

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

6 DISCUSSION AND CONCLUSIONS

In this paper we present a computational study for patient admission planning and the allocation of providers in outpatient clinics that considers the operation of the clinic front desk. An IP model was developed that takes into consideration two types of patients “new” and “existing” with walk-ins and no-shows. The goal is to reduce the waiting time at the clinic by balancing the number of new patients arriving at the same time for their check-in taking into consideration walk-ins and no shows. A multispecialty clinic is considered with multiple doctors with independent schedules and preferences in terms of appointment durations. The results of this research show that there is a trade-off between the maximum number of new patients that can be scheduled per appointment time 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 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.

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