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A COORDINATED SCHEDULING POLICY TO IMPROVE PATIENT ACCESS TO SURGICAL SERVICES

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ABSTRACT

This paper presents a scheduling policy that aims to reduce patient wait time for surgical treatment by coordinating clinical and surgical appointments. This study is of interest since the lack of coordination of these resources could lead to an inefficient utilization of available capacity, and most importantly, could cause delays in patient access to surgical treatment. A simulation model is used to analyze the impact of the policy on patient access and surgical throughput.

1 INTRODUCTION

As identified in IOM (2001), timely access to care is one of the fundamental characteristics of high-quality health care delivery. However, access to care is a complex notion since it encompasses several facets that influences the entry or usage of health care services, for example, medical need, availability of resources, cost and quality of services, provider and patient preferences, and physical access (Dutton 1986; Kullgren, McLaughlin, Mitra, and Armstrong 2012; Levesque, Harris, and Russell 2013).

In this work, access to care is defined as the time needed to schedule an appointment with a health care resource, such as, physician, medical equipment, and operating room. Under this definition, access is related to matching the available capacity with patient needs which is a difficult task given the inherent uncertainties within health care delivery processes (Mays, Smith, Ingram, Racster, Lamberth, and Lovely 2009). Currently, the US is experiencing a shortage of health care providers (Charles, Walker, Poley, Sheldon, Ricketts, and Meyer 2011; AAMC 2015), while demand for medical care is increasing sharply due to an aging and growing population (Strunk, Ginsburg, and Banker 2006). As reported in Merrit-Hawkins (2014), VHA (2016) the limited capacity combined with high demand is currently creating barriers to access care. For example, the average patient appointment wait time of the fifteen large metropolitan areas surveyed in Merrit-Hawkins (2014) exhibit an increasing trend over the years.

Timely access to care does not only affect patient satisfaction (Thompson and Yarnold 1995; Anderson, Camacho, and Balkrishnan 2007), but patient health outcomes as well. The surveys examined in Oudhoff, Timmermans, Knol, Bijnen, and van der Wal (2007), Lynch, Campbell, Clark, Dunbar, Goldstein, Peng, Stinson, and Tupper (2008) shows that some patients could experience medical complications while waiting for care, which cause significant deterioration in health related quality of life and psychological well being.

The mismatch of institutional supply-demand and its effects on patient health outcomes emphasize the importance to design appropriate policies to better utilize and coordinate the resources available. Scheduling practices play an important role to ensure timely access to care, inefficient practices could cause unnecessary delays and waste capacity (IOM 2015). The complex nature of the scheduling problem in health care has attracted researchers from different backgrounds, and there is a rich literature on appointment scheduling. Green and Savin (2008) formulated a queueing approach for appointment scheduling in primary care medicine. Barz and Rajaram (2015) analyzed an admission scheduling problem. An optimal timing of appointments is addressed by Denton and Gupta (2003). An operating room scheduling is studied in (Shylo, Prokopyev, and Schaefer 2013). The interested reader is referred to Defraeye and Nieuwenhuyse (2015), Cardoen, Demeulemeester, and Beliën (2010), Gupta and Denton (2008) for a literature review on scheduling problems in health care.

This paper is structured as follows: the problem that motivated this analysis is formulated in section 2. Section 3 outlines the key components of the scheduling process. The performance of the scheduling policy is reported in section 4. Final remarks and future directions are given in section 5.

2 PROBLEM DESCRIPTION

This study addresses the scheduling problem of patients referred to a surgical specialty division (SSD) of the Department of Surgery at Mayo Clinic. Patients under medical care who are referred to SSD present a medical condition for which surgery is a treatment option. In general, the surgery process begins with a clinical appointment; patients are paired with a surgeon who specializes in patient's surgical indication and the corresponding treatment procedures. During the clinical appointment the surgeon discusses treatment options with the patient and also evaluates if surgery is a feasible option; if feasible, the surgery is scheduled after the patient signs a consent form.

The scheduling process analyzed starts when a clinical appointment is requested, as illustrated in Figure 1. At that point, a scheduling coordinator collects the patient indication and provides possible dates for an appointment with available surgeons. After the patient is seen in clinic a patient-surgeon relationship is established, and surgery might be scheduled based on joint decision of patient and surgeon. The main objective is to study the impact of scheduling policies on clinical and surgical access.

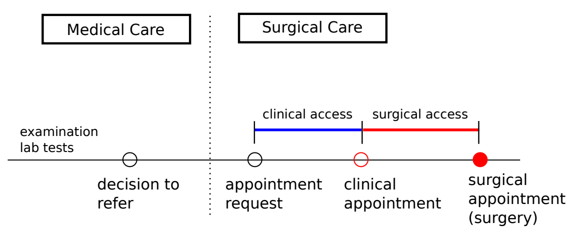

Figure 1: Wait time is measured from appointment request to surgery.

The current scheduling process of the SSD prioritizes access to clinic, which will be referred to as "earliest clinic" policy in this paper. The earliest clinic policy suggests surgeons with clinical appointments available close to the appointment request date. This policy optimizes clinical access, this is, it creates a clinical appointment with a surgeon such that the time from appointment request to clinical appointment is minimized. The general algorithmic scheme of the earliest clinic policy is described in Algorithm 1.

Although the SSD had reported appropriate clinical access, measured with "3$^{\text{rd}}$ Next Available Appointment" standard (IHI 2016), patients could experience delays to receive the surgical treatment needed. Figure 2 shows a supply-demand analysis of the SSD, the red and blue lines represent the number of surgeries performed and new surgical cases generated after a clinical appointment, respectively. The green line displays the increasing trend of the wait time for new surgical cases to be performed. The current average wait time is approximately four weeks, for this reason the SSD is putting a high priority on adapting the current scheduling policy to improve surgical access.

Algorithm 1 Earliest Clinic

1: Appointment request: request-date = (mm,dd,yyyy).
2: Collect patient's information: surgical indication.
3: Set $\delta =$ request-date.
4: Clinical access: Select surgeon in SSD if:

$$C_{\text{calendar}}[\text{surgeon}, \delta] - 1 \geq 0,$$

where C_{calendar} is the clinical calendar of the surgeon with capacity measured by the total number of appointments available on a clinical day. If there are not clinical appointments available then set $\delta \to \delta + 1$ and go to Clinical access; otherwise, select surgeon.
5: Patient-surgeon: Pair patient with surgeon with clinical availability. Book clinical appointment at day δ.
6: Patient seen: If patient does yield surgery then find $d \geq \delta + 1$ such that:

$$S_{\text{calendar}}[\text{surgeon}, d] - T_s \geq 0,$$

where S_{calendar} is the surgical calendar with capacity measured in hours, and T_s is the duration of the surgical procedure to be performed.

As an example of patient flow with the earliest clinic policy, simulated patients sampled from historical data are shown in Table 1. The displayed dates correspond to business days (each month has 20 working days). It can be observed that the wait time from appointment request to surgery ranges from two weeks up to eight weeks. The main drawback of the earliest clinic policy is the lack of coordination between the clinical and surgical calendars of surgeons. For example, Patient 1 and 2 have to wait over a month to gain access to surgery because the surgical calendar of Surgeon 1 is fully booked for one month.

Table 1: Earliest clinic policy: patient flow example.

Patient ID	Request Date	Clinical App.	Surgical App.	Surgeon ID
Patient 1	Month 1, Day 1	Month 1, Day 1	Month 2, Day 10	Surgeon 1
Patient 2	Month 1, Day 1	Month 1, Day 1	Month 2, Day 20	Surgeon 1
Patient 3	Month 1, Day 2	Month 1, Day 2	Month 1,Day 15	Surgeon 4
Patient 4	Month 1, Day 2	Month 1, Day 2	Month 1, Day 13	Surgeon 4

In order to control the wait time from appointment request to surgery, the proposed coordinated scheduling policy selects surgeons with surgical appointments available close to the appointment request date, and a clinical appointment available anytime between appointment request and the selected surgical appointment. In contrast to the earliest clinic policy, this policy creates a patient itinerary composed of a clinical appointment and a tentative surgical appointment. The surgical appointment of the patient itinerary is reserved in the surgical calendar of the selected surgeon until the patient is seen in clinic. After the clinical appointment the surgery could be confirmed or the surgical appointment could be canceled.

Coordination of clinical and surgical calendars is only possible if the potential surgical need of patients can be inferred at the time of appointment request. To this end, historical clinical and surgical data of the SSD was used to determine *surgical yield* and *duration of surgical procedures*. The estimation of the surgery-related parameters needed to implement the coordinated policy is described in section 3.2. The general algorithmic scheme of the coordinated policy is detailed in Algorithm 2.

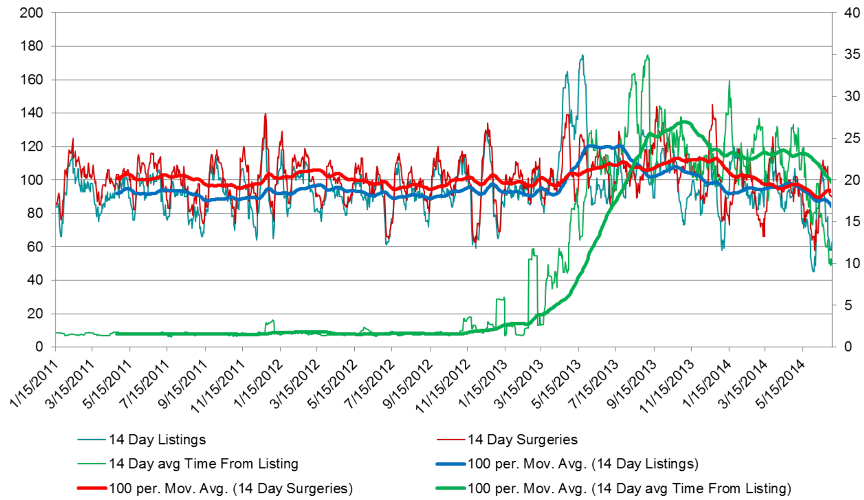

Figure 2: SSD surgical access analysis.

Algorithm 2 Coordinated Policy

1: Appointment Request: request-date = (mm,dd,yyyy).
2: Collect patient's information: surgical indication.
3: Determine surgery duration: T_s.
4: Set $d = \text{request-date} + 1$.
5: Surgical access: preselect surgeon if:

$$S_{\text{calendar}}[\text{surgeon}, d] - T_s \geq 0.$$

6: Clinical access: Find $\delta \in \{\text{request-date}, \ldots, d-1\}$ such that

$$C_{\text{calendar}}[\text{surgeon}, \delta] - 1 \geq 0,$$

if δ does not exist then set $d \to d+1$ and go to Surgical access; otherwise, select surgeon.
7: Patient-surgeon: Pair patient with surgeon with clinical and surgical availability. Create patient itinerary (δ, d): book clinical appointment at day δ and reserve surgical appointment at day d.
8: Patient seen: If patient does not yield surgery the surgical appointment is canceled: $S_{\text{calendar}}[\text{surgeon}, d] \to S_{\text{calendar}}[\text{surgeon}, d] + T_s$.

Table 2 illustrates the surgeon-patient assignment obtained with the coordinated policy. As expected, this policy can significantly reduce patient wait time. For example, Patient 1 and 2 would be able to access to surgery in two weeks if they are assigned to Surgeon 6. This example shows the importance of coordinating clinical and surgical calendars for a more efficient patient flow.

Table 2: Coordinated policy: patient flow example.

Patient ID	Request Date	Clinical App.	Surgical App.	Surgeon ID
Patient 1	Month 1, Day 1	Month 1, Day 1	Month 1, Day 14	Surgeon 6
Patient 2	Month 1, Day 1	Month 1, Day 1	Month 1, Day 14	Surgeon 6
Patient 3	Month 1, Day 2	Month 1, Day 2	Month 1, Day 15	Surgeon 4
Patient 4	Month 1, Day 2	Month 1, Day 2	Month 1, Day 14	Surgeon 7

3 METHODOLOGY

The goal of the simulation is to analyze if implementation of the coordinated policy would improve utilization of the SSD resources since several variables, such as, clinic fill rate, surgical yield, medical complexity of patients, capacity of calendars, play a significant role in the scheduling process.

The SSD division has eight surgeons, which are labeled as “Surgeon j”, $j = 1, \ldots, 8$. Surgeons of this division are trained to performed all the surgical procedures offered by the division. Based on anecdotal evidence of members of the SSD, patient’s preferences to be attended by a particular surgeon can be omitted for most of the cases because nearly 80% of SSD patients travel from other countries or different regions of the US to receive medical treatment at Mayo Clinic. Therefore, for the SSD modeled in this work patient preference’s will not be considered. For a fair comparison of the scheduling policies, the capacity of calendars is fixed in the simulation and are the same for both scheduling policies.

Four years of clinical appointment data was used to represent the characteristics and arrivals of the patient population. The surgeon calendars were generated using four years of clinical appointment data and billing data of surgeries performed by the SSD in 2015. The simulation models the interaction between the four main components described in the following sections: 1) patients, 2) duration of surgical procedure and surgical yield, 3) capacity of surgeons calendars, and 4) scheduling process that determines patient-surgeon assignment.

3.1 Patients

The patient population of SSD can be classified as “new” or “return”. New patients require services offered by SSD, therefore, this group needs access to clinic and probably access to surgery; return patients have an established patient-surgeon relationship with a surgeon in SSD, this group captures postoperative patients and follow-up visits and only needs access to clinic. New patients represent 55% of the population; the remainder are return patients. Furthermore, SSD division deals with patients with complex medical care since 70% of patient who had surgery are admitted as inpatient or are already admitted in the hospital under care of another division. This is also reflected in clinical appointment data because only 5% (approximately) of patient missed or canceled their appointment. In the simulation model, patient arrivals are modeled as a Poisson process with different intensities for each day of the week. Each patient is classified as new according to a Bernoulli variable with probability of success equal to 0.55. New patients are assigned a surgical indication, a surgery duration T_s, which is sampled from a distribution of the surgical indication, and surgical yield probability, see section 3.2 for more details. Return patients are assigned a surgeon with a probability estimated from historical data on patient volume attended in clinic by each surgeon.

3.2 Surgical Parameters

The estimation of the surgical parameters required a data set comprised of several sources in order to obtain an accurate understanding of the surgical process. Clinical appointment data was used to map out the patient flow through the SSD and determine surgical yield. Multiple sources of surgical data were used to obtain distributions around the surgical procedures related to patient appointments. The SSD classifies surgical procedures in broad surgical categories, which they will be generically denoted as $\{D_X s, s \in \mathscr{S}\}$. This classification creates difficulties to determine the surgical procedure from data since post-surgical data defines the actual surgical procedure with codes used for billing purposes. Consequently, a surgery event could contain several different procedural codes with an unclear relationship with the surgical categories. Outside of performing chart reviews for thousands of surgical cases, there was no easy way to define each surgery precisely.

However, using the expertise of individuals within the SSD a mapping from billing codes to surgical categories was defined. This mapping enabled the clustering of surgical procedures (billing data) into specific surgical categories. Unfortunately, this still resulted in some surgical procedures being defined as multiple surgical categories, the obtained clusters were not disjoint. For example, a surgery event may be defined as both $D_X s_1$ and $D_X s_2$. Using the expertise of members in SSD an assumption was made that the surgical categories would be placed into a hierarchical order: $\mathscr{P}(D_X 1) > \cdots > \mathscr{P}(D_X S)$. Thus if a surgery was both $D_X s_1$ and $D_X s_2$, it could be defined as $D_X s_1$ if $\mathscr{P}(D_X s_1) > \mathscr{P}(D_X s_2)$. The application of the billing mapping and the hierarchical order resulted in well-defined empirical distributions for the surgical categories.

For example, the surgical duration distribution of $D_X 1$, the surgical category with the highest order, is shown in Figure 3; it can be observed that the billing mapping with the hierarchical order derived an adequate sampling. Furthermore, $D_X S$, which had a low order, also had a very good distribution, even though the mapping approach reduced the sample size significantly, see Figure 4. The distributions were calculated using Expert Fit 8.01, surgical duration is measured in minutes. The surgical duration distributions were

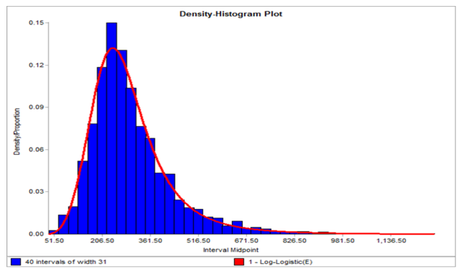

Figure 3: Surgical duration for highest-order surgical category.

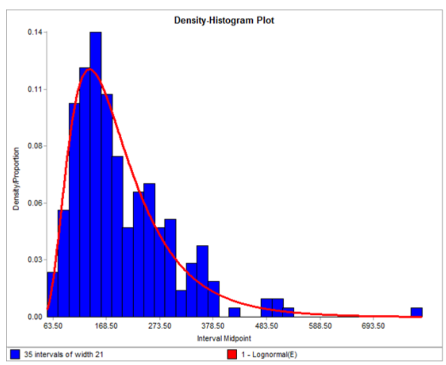

Figure 4: Surgical duration for lowest-order surgical category.

generated for each procedure, it was not possible to built distributions per surgeons due to lack of data. In the simulation model the surgical duration of each procedure was scaled to reflect differences between surgeons. For a given pair $D_X s$ and Surgeon j, the scale factor is defined as 1 if data was not available; otherwise, it is equal to $\mathbb{E}[D_X s \cap \text{Surgeon } j]/\mathbb{E}[D_X s]$. The scale factors empirically capture if a surgeon performs a surgical procedure below or above its average duration. Table 3 reports the expected duration of the ten surgical procedures of SSD (measured in minutes). The rows $\text{Scale}_{j,s}$, $j = 1,7,8$, have examples of the scale factors used per procedure for Surgeon 1, 7, and 8.

Table 3: Surgical Procedures: expected duration [min], and surgeon-scale factors.

	$D_X 1$	$D_X 2$	$D_X 3$	$D_X 4$	$D_X 5$	$D_X 6$	$D_X 7$	$D_X 8$	$D_X 9$	$D_X 10$
$\mathbb{E}[D_x s][min]$	300	262	309	200	256	246	68	115	91	161
$\text{Scale}_{1,s}$	1.42	1.32	1.36	1.20	1.14	1.01	1.31	1.81	1.55	1.21
$\text{Scale}_{7,s}$	0.87	0.89	0.91	0.81	1.0	1.0	0.97	0.76	0.93	1.0
$\text{Scale}_{8,s}$	0.79	0.85	0.86	0.72	0.87	1.0	0.85	0.68	0.64	0.80

Patients were assigned a surgical indication equal to the surgical category with a probability estimated with the size of the sample used to built the distributions, also the duration of the surgery needed to treat the patient (T_s) was sampled from the distributions of the surgical categories described above. Determination of surgical yield was also quite difficult since linking a specific clinical appointment with an eventual surgery is not straightforward. Patients may have several appointments before the decision to have a surgery takes place or an appointment may occur in another department (or clinic) which would then refer a patient to SSD for a surgery. So the assumption made was that if a patient had an appointment on or within two weeks of the date of surgery was scheduled then that appointment yielded a surgery. Consequently in order to not over count the non-surgical patients, it was only considered the most recent clinical appointment of patients as an observation. The end result is that each patient would have one appointment counted and it was obtained a patient's yield rather than an appointment's yield. The resulting surgical yield was 68.3%, which was verified by those within SSD as a realistic parameter.

3.3 Surgeon Calendars

Mayo clinic uses an every-other-day operating calendar for surgeons called blue-orange shifts; surgeons perform surgeries on one day and on the next one they have clinical appointments with patients. The calendars were populated according to the blue-orange shift of each surgeon.

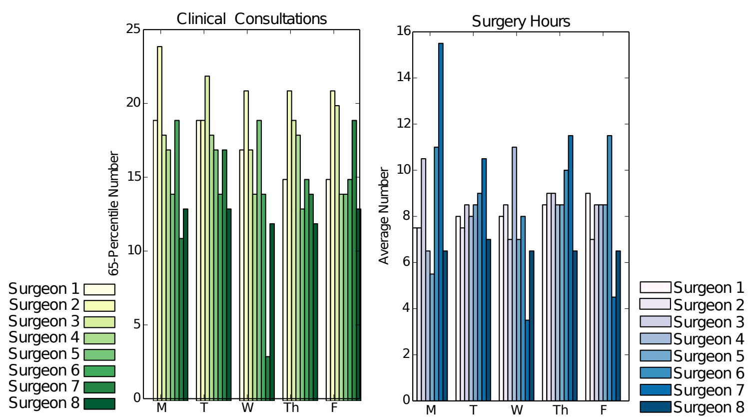

Figure 5: Clinical and surgical capacity.

The clinical capacity was set to be the 65$^{\text{th}}$ percentile number of patients seen in clinic per day per surgeon, based on observations that SSD has more flexibility in extending clinical capacity when necessary. The surgical capacity was set as the average hours of operating room utilization per day per surgeon, as shown in Figure 5. These parameters were selected so the performance of the earliest clinic policy captures the monthly-average surgical throughput of SSD in 2015.

3.4 Scheduling Process

New patients are assigned a surgeon as described in Algorithm 1 and 2. The approach implemented to select a surgeon when multiple feasible calendar openings are available is described below:
Earliest clinic. Clinical access step: given δ find $j^* \in \{1,\dots,8\}$ such that:

$$j^* = argmax\{\Delta_j | \Delta_j = C_{\text{calendar}}[\text{Surgeon } j, \delta] - 1 \text{ if } \Delta_j \geq 0\}. \quad (1)$$

Coordinated policy. Surgical access step: given d find $j^\star \in \{1,\dots,8\}$ such that:

$$j^\star = argmax\{D_j | D_j = S_{\text{calendar}}[\text{Surgeon } j, d] - \text{Scale}_{j,s} * T_s \text{ if } D_j \geq 0\}. \quad (2)$$

The scheduling policies assume that return patients prefer a clinical appointment as soon as possible. The selection of a clinical appointment for this group of patients is as follows:

Return patient. Let Surgeon j_r be the surgeon of the return patient requesting a clinical appointment. Let $\delta =$ request-date, and compute the quantity given below:

$$\Delta = C_{\text{calendar}}[\text{Surgeon } j_r, \delta] - 1, \tag{3}$$

if $\Delta \geq 0$ stop; otherwise, set $\delta \rightarrow \delta + 1$ and go to equation (3).

Mayo Clinic uses a 12-week rolling scheduling horizon. Surgeon calendars are maintained on a 16-week rolling planning horizon and they are updated on a monthly basis so that patient can have access to clinic and/or surgical services twelve weeks into the future (Martinez, Bernard, Larson, Pasupathy, and Sir 2016). Therefore, the feasible time frame to schedule a clinical or surgical appointment is within 12 weeks from appointment requesting date: $\delta < d$, $|\text{request-date} - \delta| \leq 12$ weeks and $|\text{request-date} - d| \leq 12$ weeks.

3.5 Simulation Model

The simulation time period is measured in months where each month has 20 business days with 9 working hours. The total number of appointment requests (patient arrival) is generated for each day of the month in the simulation time period. Patients are scheduled in the order they arrive: each new patient is scheduled using Algorithm 1 with selection rule (1) and Algorithm 2 with selection rule (2), and return patients are given a clinical appointment as described in section 3.4 selection rule (3). Scheduled patients seen in clinic are reviewed each day: Step 6 of Algorithm 1 is applied for patients scheduled with the earliest clinic policy; Step 8 of Algorithm 2 is employed for patients scheduled with the coordinated policy.

4 RESULTS

The simulation model was implemented in Python 2.7.6 with Scipy, Pandas and Seaborn packages. The first three months of the calendars were booked to reflect the status of SSD as in October 2015. The scheduling system was simulated for a period of time of 5 years to analyze the effect of coordination under the assumption of calendars with fixed capacity. The performance of the policies were compared with values on wait time to clinic, wait time to surgery, and surgical throughput.

Figure 6 reports the daily moving average of wait time to access clinic for new patients. On average, the earliest clinic policy can guarantee a clinical appointment one day whereas the coordinated policy has a higher wait time to clinic for the first months of the simulation and it reduces gradually. This trend is direct result of the time needed for coordination between clinical and surgical calendars to take effect. The coordinated policy delays access to clinic for surgeons with fully booked surgical calendars and it limits the number of clinical appointments assigned since it is aware that surgical calendars do not have capacity to accommodate more patients.

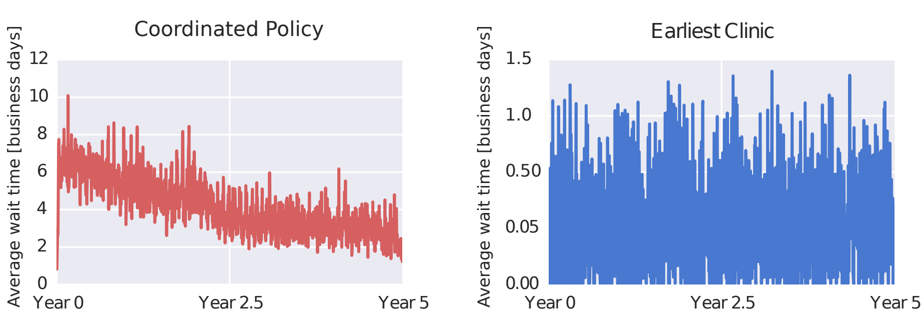

Figure 6: Access-to-clinic time moving daily average of scheduled patients in clinic.

For return patients, the earliest clinic policy can provide a clinical appointment on the same day. The coordinated policy can not guarantee same day access to clinic for this group of patients; a consequence of prioritizing access to surgery is that new patients tend to have a priority access to clinic, so some return patients have to wait up to two weeks during the first year of the simulation time. This result suggests that SSD might need to use other health care resources, such as, physician assistants to accommodate return patients, at least in early stages of the implementation of a coordinated policy.

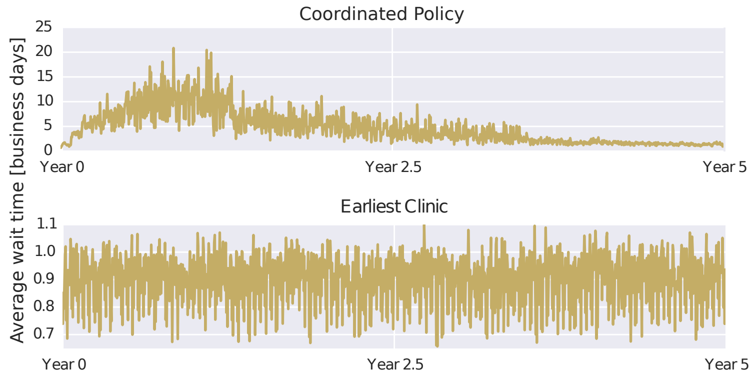

Figure 7: Return patients access-to-clinic moving daily average of scheduled return patients.

Figure 8 reports the daily moving average of wait time from clinic to surgery, for new patients. The coordinated policy provides better access to surgery and the wait time has a decreasing trend. This indicates that the coordinated policy can balance the surgical load more fairly among surgeons than the earliest clinic policy.

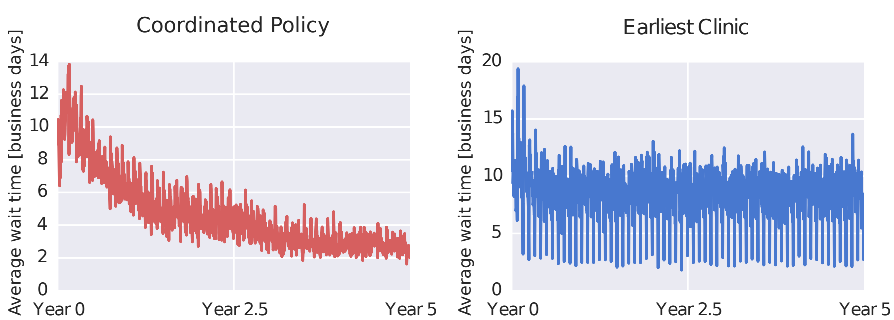

Figure 8: Access-to-surgery time moving daily average of scheduled patients in surgery.

The box-plots in Figure 9 show the simulated realizations of wait time from appointment request to surgery. The coordinated policy shows a smaller variance on the values, the extreme values (wait time larger than 35) is caused by the initial condition of the calendars. According to the simulation results, the positive effect of the coordinated policy would be evident after the first year of its implementation, assuming calendars with fixed capacity.

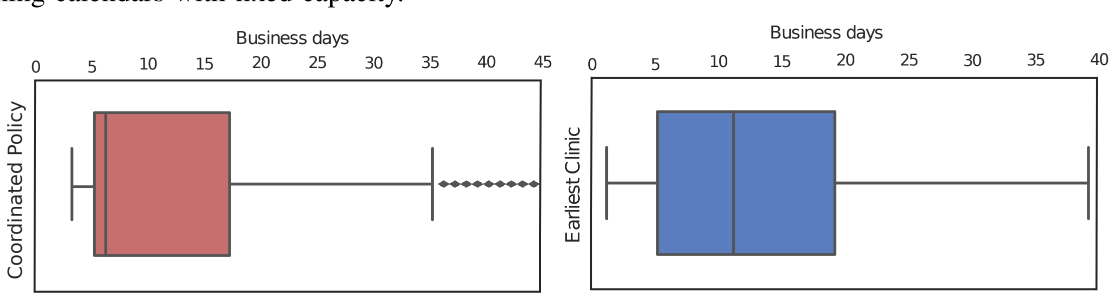

Figure 9: Appointment request-to-surgery time of scheduled patients in surgery.

The effect of the coordinated policy per surgeon is reported in Table 4. In general, the coordinated policy performs better than the earliest clinic, for example, the wait time from appointment request to surgery can be reduced by 46% for Surgeons 1,2, and 3, it can be reduced by 70% for Surgeons 6 and 8, and it does not show any significant change for Surgeons 4 and 5. As previously observed, the average wait time to surgery with the coordinated policy is significantly smaller than the one with the earliest clinic but wait time to clinic tends to be higher, and in some cases it is unacceptable (Table 4 - Surgeon 7).

Table 4: Comparison of policies per surgeon: average wait time is measured in business days.

	Earliest clinic		Coordinated			Earliest clinic		Coordinated	
Average wait	clinic	surgery	clinic	surgery	Average wait	clinic	surgery	clinic	surgery
Surgeon 1	0.36	17.72	0.91	7.07	Surgeon 5	0.46	7.24	4.41	3.38
Surgeon 2	0.46	15.71	1.04	6.91	Surgeon 6	0.36	11.78	1.44	6.93
Surgeon 3	0.378	17.08	0.89	7.05	Surgeon 7	0.55	20.53	21.89	1.42
Surgeon 4	0.54	7.67	5.60	2.89	Surgeon 8	0.45	9.52	4.65	3.27

Figure 10 shows the difference between the number of surgical and clinical appointments scheduled per month by the coordinated policy and the earliest clinic policy for Surgeons 1, 7, and 8. The surgical throughput of Surgeon 1 and 8 can be improved with the coordinated policy, with a significant benefit for Surgeon 8. The consumption of clinical appointments changes with the coordinated policy, and it can be observed that within a year of calendar coordination the fill rate of clinic is similar to the earliest clinic policy. In addition, the simulation results suggest that SSD should implement a combined policy, for example, the earliest clinic policy seems to be better suited for the calendar structure of Surgeon 7. As

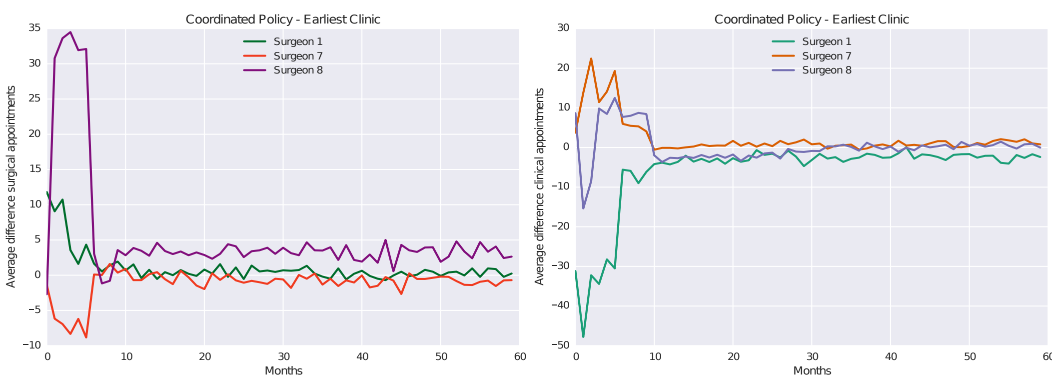

Figure 10: Coordinated policy versus earliest clinic: surgical and clinical appointments.

illustrated in Figure 11, the coordinated policy allocates the surgical cases more efficiently; with the same calendar capacity the SSD could increase its throughput on average by 3 cases per month.

5 CONCLUSIONS

The simulation results indicate that coordination of calendars is beneficial for creating itineraries for patients requiring surgical treatment. Although the number of surgeries performed per month with the coordinated policy is increased only by 3 cases per month, the general improvement in wait time from appointment request to surgery makes this policy a good fit for SSD to meet its access goals. The clinical access of Surgeon 7 is poor with the coordinated policy, and it does affect the overall moving average reported in Figure 6. On the other hand, surgical access of Surgeon 7 is poor with the earliest clinic policy, these results suggest an inherent calendar inefficiency of Surgeon 7. In addition, the coordinated policy is likely to utilize approximately 93% of the surgical capacity, wasted capacity accounts for 7% and it is due to patients who do not yield surgery and the gap between their clinical and surgical appointment is within two

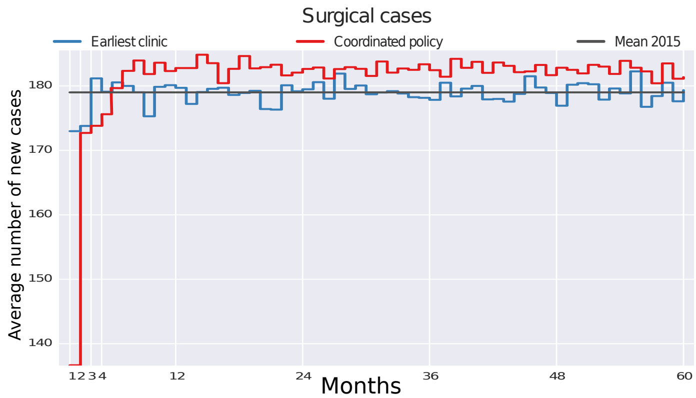

Figure 11: Surgical throughput comparison.

business days. Further evaluations are needed to measure the efficiency of the coordinated policy under real-world scheduling setting, for example, patient's information at the time of appointment request might be inaccurate resulting in not-well defined indications which impacts the estimation of surgical need of the patient. Also, the coordinated policy does not consider medical need of patients, therefore, all patients will experience similar wait times regardless of their condition.

ACKNOWLEDGMENTS

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