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SIMULATION MODELING AS A DECISION TOOL FOR CAPACITY ALLOCATION IN BREAST SURGERY

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ABSTRACT

Increased surgeon workload can result in prolonged access times for patients and may lead to surgeon burnout. Management of access times through investments in care capacity and hiring of providers require an understanding of the patient access times resulting from a given level of care capacity under different patient demand scenarios. We explore the effectiveness of a simulation-based framework in providing workforce planning insights. Our framework involves modeling of patient demand by considering different groups of surgical procedures, a simulation model that allows calibration of certain parameters through the use of data, and consideration of different demand and capacity scenarios to provide an understanding of the range of patient access times that can be expected over the immediate future during the time horizon. Our results show that such a simulation-based framework can help ground workforce planning and capacity investment decisions on operational data, and help healthcare institutions manage such costs.

1 INTRODUCTION

Timeliness of access to care is one of the main indicators of healthcare quality. Due to increasing patient demand and demand for more complex services, significant mismatch between the available care capacity and patient demand is observed, that results in prolonged delays in access to healthcare services. While addressing the mismatch, it is critical to recognize the differences in patient care needs and service complexity, and variability in service durations due to those differences. Characterizing the patient demand in terms of this observed variability is important to determine the required capacity to improve patient access.

This study was conducted in the breast surgical practice in an academic medical center. In recent years, the number of patients with complex problems (higher stage disease and recurrent cancer, see, Figure (1a)) and complex procedures (immediate reconstruction, many with nipple-sparing mastectomy, see, Figure (1b)) have increased substantially in the division. This increase in the complexity of cases has, in turn, increased the workload of providers, resulting in increases in patient care timelines and increased physical and cognitive workload for surgeons.

The increased workload may lead to both patient delays and surgeon dissatisfaction, therefore, it needs to be monitored carefully. Additionally, the mismatch between the available capacity and the workload may result in delays in care and prolonged access times for patients. To this end, we build a simulation based tool to assist the workforce management in breast surgery practice, since it is not straightforward

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(a) Change in percentage of cancer cases 2008-2018.

(b) Change in percentage of complex cases 2008-2018.

to observe the direct impact of the surgeon availability on patient access times. Due to their flexibility, simulation models allow us to represent system specific features in a model. However, it is important to limit model complexity which could quickly get prohibitive due to data and computational needs.

In order to capture the relationship between demand, capacity, and the resulting access times, we first start with modeling the patient demand considering the differences in patients' surgical complexities. Since increasing case complexity is a determinant in increasing access times, the patient demand should be taken into consideration in terms of both volume and complexity. We use a regression tree based approach to group patients into surgical complexity groups that are different in terms of surgical duration. Then, we use a forecasting model to estimate future demand of each patient group.

We build the initial simulation model to represent the current patient flow from the time that the patient is initially scheduled for surgery. The model performance is validated by comparing the resulting access times for each group with the access times that are calculated from historical transactional data. We show that our relatively simple simulation model is able to characterize the complex patient flow within the system. After obtaining a reliable model that resembles the actual system, we use our model to estimate the future performance of the system under given demand and care capacity scenarios.

Under the determined surgical complexity groups and the forecasted demand for these groups, we use the simulation model to analyze how to make case assignment in terms of both demand volume and case complexity among multiple surgeons with predetermined, fixed capacity to achieve lower access times. This allows us to observe whether the targeted access times are achievable under the determined capacity or whether workforce adjustments are needed to achieve desired access delays.

The rest of this paper is organized as follows. In Section 2, we list the relevant literature. Section 3 describes the data used and parameters estimated from the data. Next, in Section 4, we give the details of the simulation model developed and describe the validation process. Section 5 presents the insights into the research question that we raise on capacity, demand, and access relationship. Finally, in Section 6 the discussion and concluding remarks are presented.

2 LITERATURE REVIEW

Simulation models can be effectively used in data-driven decision making to provide patient-centered high quality care (see, e.g., Marshall et al. (2015)). There exists an extensive literature on studies that model patient flow to analyze the capacity requirements to improve access related performance. Similar to our focus, studies in the literature utilize simulation models to generate insights into the required capacity to eliminate prolonged waiting times for patients and reduce access times. The capacity of interest can be number of rooms allocated to patient care, bed capacity, or provider capacity, like our focus in this study.

We first focus on quantifying the case complexity from our data in terms of surgical duration. To this end, we use characteristics of surgical operations using a tree-based model to predict the duration of the surgery. Similar to our study, there are many studies in the literature that employ machine learning models using either operational, patient-related, or provider-related factors to predict the duration (see, e.g., Hosseini et al. (2015), Thiels et al. (2017), Bartek et al. (2019)). We use predicted durations to group surgical cases into complexity-based surgical groups and analyze patient demand with regard to these groups.

Most studies that consider the relationship between care capacity and observed access times develop simulation models to test alternative resource allocation strategies when there are single or multiple resources that are utilized in patient care. Using simulation modeling, many studies identify ideal capacity levels and allocation of available capacity to improve performance measures. Benneyan (1997) uses a simulation model to test potential strategies to reduce waiting times in a pediatric care clinic. Pendharkar et al. (2015) analyzes the effect of increasing the available capacity on patient waiting time in a sleep center where patients use multiple resources throughout their flow. The simulation model is used to identify a good candidate for capacity expansion by observing the change in waiting times when the capacity of each resource is increased. Similar to Pendharkar et al. (2015), Babashov et al. (2017) focuses on a radiation therapy clinic where there are multiple different resources are used throughout patient flow. The authors study identifying the resources that are more significant in improving patient access.

Elkhuizen et al. (2007) creates models for both operations in a specific department as well as for generic clinical settings. They study the capacity required to keep access time within a target of two weeks, and reduce backlog. Edward et al. (2008) studies a similar problem as Elkhuizen et al. (2007) in a perioperative assessment clinic where they also analyze the required appointment length that prevents from the fluctuations in service times. Steins and Walther (2013) determines intensive care unit bed capacity in four different hospitals to develop insights into how system performances changes under different bed capacity allocation settings. Simulation models are used to determine resource allocation for utilizing the available room and facilities capacity (see, e.g., Groothuis et al. (2001), Berg et al. (2010), Bountourelis et al. (2011), Berg et al. (2018)) and improve patient total time spent in the system. In Norouzzadeh et al. (2015), the authors focus on testing alternative scenarios of utilizing the exam rooms and allocating providers to service via simulation modeling to improve the resource utilization and patient waiting times.

In our study, we mainly consider the capacity of a single resource, the breast surgeon. However, we assume that these surgeons are not identical in terms of the total time allocated to breast surgery practice. Furthermore, each surgeon has their own demand stream since patients are assigned to surgeons at the time of patient's appointment request, and surgeons only operate after they establish a care protocol through a series of clinic appointments. Even though clinic workload is similar among breast surgeons, the patient mix (in terms of case complexity) varies surgeon-to-surgeon, which results in some surgeons being busier than others with respect to the time that they spend on surgeries. In Shahani et al. (2008), similar to our approach, the authors first classify patients into length-of-stay categories where they use patient characteristics as factors. They use simulation to test different bed allocations in a critical care unit.

Additionally, simulation models are used to identify the impact of alternative patient routing policies on waiting times. Roh et al. (2018) uses a simulation model to evaluate interventions such as routing patients to alternative care pathways to reduce the boarding time for mental health patients that are admitted through ED. Finally, Martinez et al. (2016) and Kazemian et al. (2017) identify the impact of controlling the clinical and surgical calendars of surgeons on patients' access times to surgery. In this study, we only focus on patient flow after the patients are listed for their surgery following a consultation visit with the surgeon. Therefore, in the flow that we study, the patients are already assigned to a surgeon and are usually operated on by that same surgeon.

3 INPUTS OF THE SIMULATION MODEL

3.1 Data Description and Surgical Categories

We study 4,152 breast surgery cases from August 2015 to May 2019. The dataset contains the breast surgery cases performed by six surgeons. We use two methods to classify these cases. The goal is to predict the surgical duration of each patient based on the type of surgical procedures. In the first method, 47 different procedure types that are done by the practice are grouped into five categories based on their surgical duration by our team of medical and surgical experts . In the second method, Recursive PARTitioning (RPART) (Therneau and Atkinson 1997) is used to develop a regression tree, which we use to predict the surgical duration of each patients. We identify six different features for the surgical procedures which can have a significant effect on the duration of a surgery. Our final decision tree has seven terminal nodes, which are referred to as groups in the rest of the paper. When we move from Group 1 to Group 7, the surgical complexity increases. To perform the surgeries for Groups 5, 6 and 7, a plastic surgeon needs to be paired with a breast surgeon while surgeries in Groups 1 to 4 are solely performed by a breast surgeon. Group 1 has the lowest surgical duration while Group 7 has the longest surgical duration. The details of the decision tree algorithm and surgical groups are studied in Kilinc et al. (2020). Group 3 is representing the largest portion of the patient population (29%) while Group 7 patients are only 1.5% of the total patient population.

3.2 Demand Forecasting Models

We use Auto Regressive Integrated Moving Average (ARIMA) to predict the demand for the seven groups identified by our decision tree. ARIMA models are used to model and forecast a time series. We search through different combinations of p, d and q parameters using a stepwise approach where p is the order of the Auto Regressive process, d is the number of differencing required to make the time series stationary and q is the order of the moving average term. We choose the model that has the least Akaike Information Criterion (AIC). AIC is an estimator to evaluate the quality of statistical models. It uses the likelihood of a model to predict future values to assess relative performance of different statistical models (Sakamoto et al. 1986). For Groups 2, 3, 4, 6 and 7, we have non-stationary trends. They transform to a stationary time series with a differencing value equal to 1. The model of Group 1 is a pure moving average model where it depends only on the lagging forecast errors and Group 7 has a pure autoregressive forecasting model. The other groups have mixed models where both autoregressive and moving average parameters are incorporated to build the model.

4 SIMULATION MODEL

We model the patient flow from the time that the surgery is scheduled to the time of the surgery. The model consists of each surgeon's separate calendar and separate demand stream since once a patient is seen by the surgeon in clinic, the same surgeon performs the surgery. At the time of scheduling the surgery, each patient is assigned to an available surgical slot in their surgeon's calendar. The surgical duration for each surgical group is determined based on the historical data as indicated in Section 3. Once the patient is assigned to an available slot in calendar, the time of surgery does not change in the model. Although cancellations, reschedules, and no-shows do occur, they are very rarely observed in the real system. Therefore, we do not take these events into consideration in our model. Finally, operating room (OR) scheduling is beyond the scope of this paper since historical data do not show any access delays occurring due to OR shortage.

The scheduling system is modeled using the weekly demand and weekly surgeon calendars. The simulation captures the period from August 2015 to December 2022. Between August 2015 and May 2019, we use the historical data on the total surgical time spent on each week to represent each surgeon's weekly capacity and historical data on demand for each surgeon from each surgical group. We did not have direct access to surgeons' calendars during the study period. Therefore, using historical weekly surgical time spent as a representative of the capacity helps us observe certain characteristics of the calendar without having direct access to certain pieces of information. For instance, we expect to observe a significant drop in the weekly total surgical time for a surgeon during the weeks that he/she is on a trip or vacation. Using historical data allows us to reflect those weeks that the surgeon operates with lower capacity in the simulation model. The simulated flow is given in Figure 2.

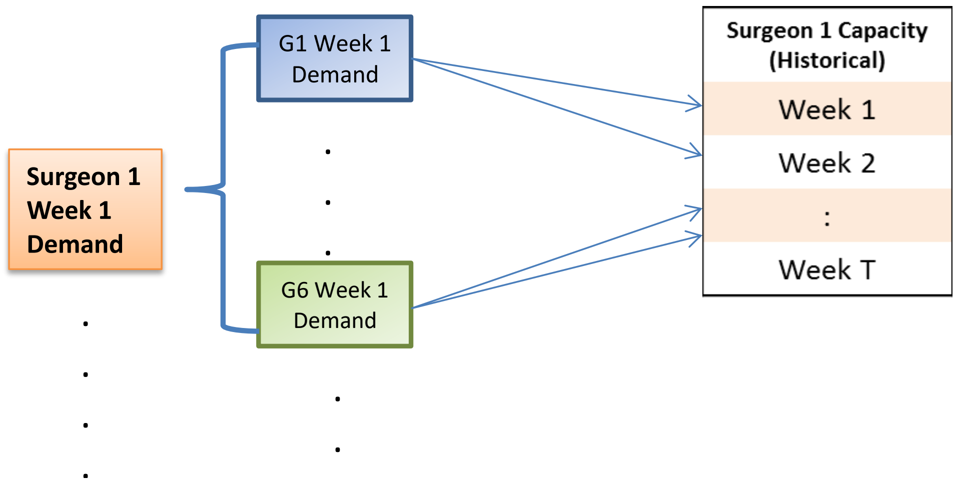


Figure 2: Patient flow in simulation model from August 2015 to May 2019.

After May 2019, we start employing the monthly demand forecasts that we describe in Section 3. Instead of using a separate forecasting model for each surgeon and each group, we simply distribute the forecasted monthly demand to each surgeon by using fractions obtained from historical data. Then, we randomly assign this monthly demand to the weeks of that month. Additionally, we use the planned yearly surgical capacity for each surgeon to represent surgeons' weekly availability since we do not have access to planned surgeon calendars with the details on trip and vacation days. Instead, for each surgeon, we have the total number of clinical workdays per year and proportion of their time allocated to breast surgery in terms of full time equivalent (FTE) after taking into account anticipated vacation and business related trip time. We assume that this yearly total capacity is distributed equally among the weeks. This assumption may not be realistic since the trip and vacation time reduces surgeons' availability on a temporal/weekly basis, however, we do not have access to the exact planned calendars to represent this detail in the simulation model and therefore it represents a reasonable assessment over months to a year, rather than on a weekly basis. The modeled flow is illustrated in Figure 3. Scheduling of patients in the breast surgical practice is

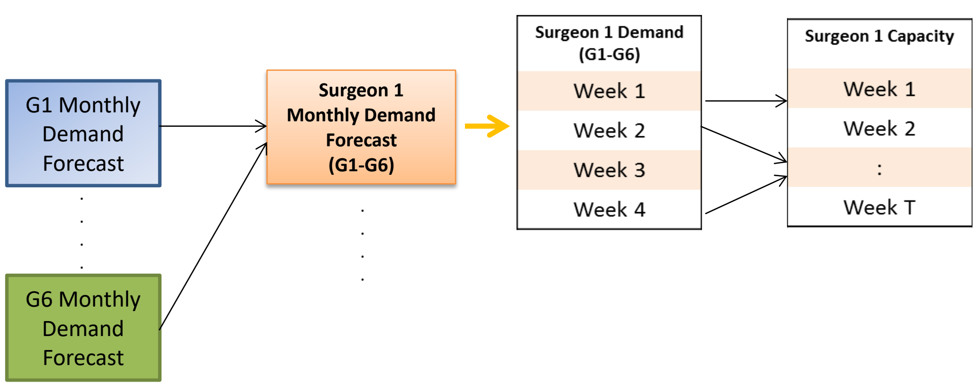


Figure 3: Patient flow in simulation model after May 2019.

generally guided by next available time, taking into account specific patient needs such as addition of the plastic surgeon or adequate time after completion of chemotherapy. In our simulation model, we use first come first served (FCFS) service policy while assigning patients from surgical groups 1-4. The surgical categories that are grouped under groups 5-7 are the ones with reconstruction and require a plastic surgeon to be in attendance during the operation. We represent this dynamic in the model with probabilities that represent plastic surgeon availability. We assume that the probability of finding a plastic surgeon increases over time (i.e., higher probability for each successive week) and it is more likely to find a plastic surgeon available for less complex cases (i.e., higher probability for Group 5 than Group 6). Figure 4 illustrates the described flow. Throughout our simulation results, we do not report the access time metrics for Group 7 patients since the procedures that fall under Group 7 are done relatively rarely.

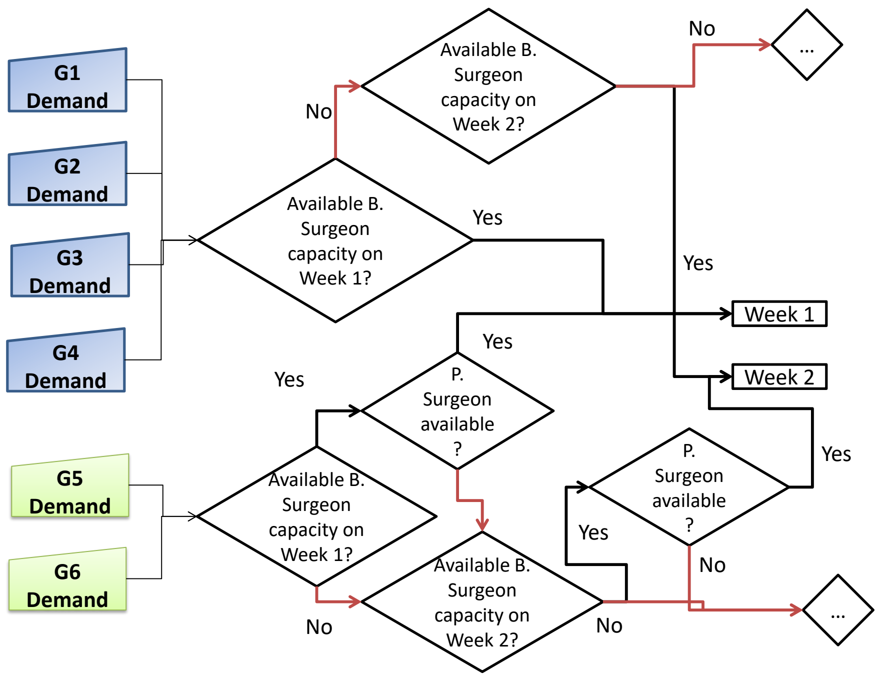


Figure 4: Patient assignment to calendar.

4.1 Validation

It is critical to ensure that the simulation model successfully represents the real system. We represent the system with a rather simple flow in the simulation model since it is not possible to discover and model the entire dynamics of this complex system from the available data. Since we have data on historical access times for each patient group, we use this metric to validate and test our model.

Due to sudden increases in patient demand or surgeon being not available due to trip/vacation, the monthly access times for some groups can dramatically increase or decrease. In order to avoid this, we report access times for each group by using a 12-month moving average and compare these averages from the historical data with the simulation outputs. The simulation is run from August 2015 to December 2022 with a six month warm-up period and 100 replications.

One of the main challenges in the simulation model is to determine the historical surgical duration for each group and historical actual surgical time spent on each week by each surgeon. There are two main time metrics collected to represent the duration of a surgery, which are incision to close (IC) and wheels in to wheels out (WW). IC is the time between the surgeon making an incision and to the closure of the incision. WW can be defined as the duration between the time at which patients are rolled in to the operating room (OR) until the time that they leave the OR. The actual of amount time that the surgeon spends on a specific surgery can be anywhere between IC and WW values.

We use median WW as the duration of each group while modeling scheduling decisions to represent the whole time that the patient spends in the OR. For the surgical capacity used, we first start with total weekly IC for each surgeon, then we adjust this metric by slightly increasing it to get access metrics closer to historical data. The second parameter that we fine-tune to reflect the uncertainty in the system and bring our simulation results closer to historical access metrics is the probabilities that represent plastic surgeon availability for surgical groups 5, 6 and 7.

While presenting our results, we do not directly report the access times to avoid revealing sensitive or confidential information. Instead, we report the percent difference between simulated and actual access times. We present the results from January 2017-January 2019 period in Figure 5, where we plot the value of percent differences from actual access times, i.e., (actual-simulated)/actual.

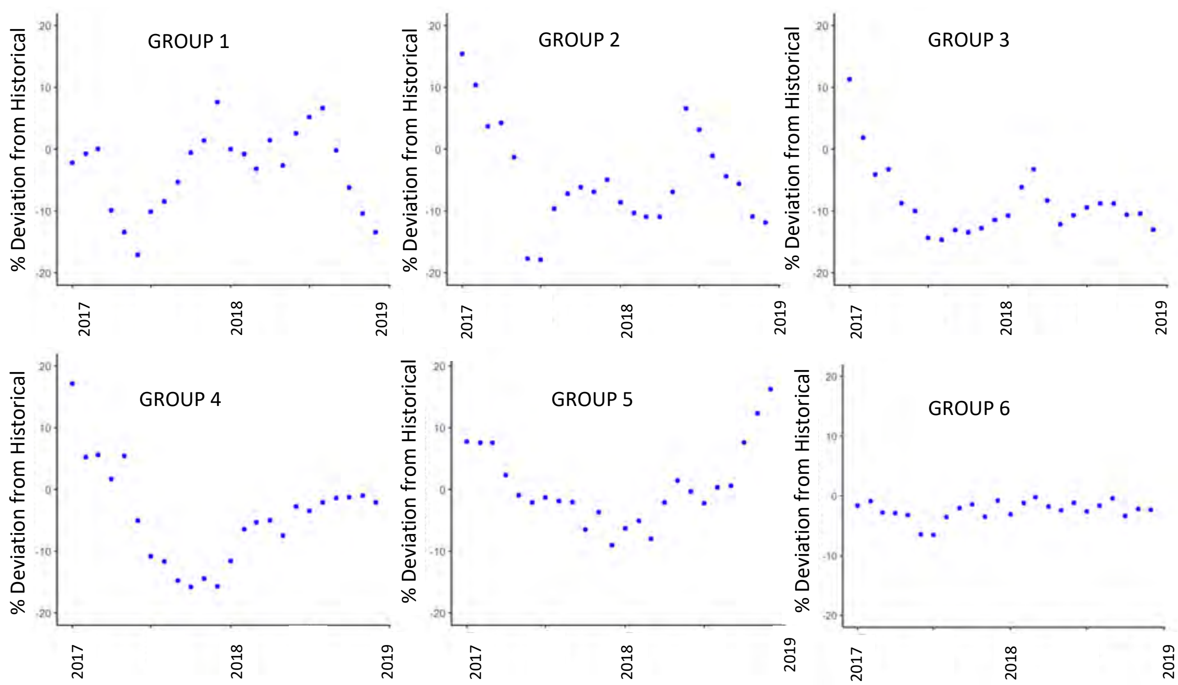


Figure 5: Deviation of the simulated estimates from the historical access times for each surgical group.

Our analyses show that all of our access time estimates are within 20% the actual access times; 75% of the estimates are within 10% and the average percent deviation is 6%. From these observations, we conclude that simulation model sufficiently reflects the dynamics of the real patient flow, and can be used to generate insights to support investment decisions on care capacity.

4.2 Scenario Evaluation

We generate alternative scenarios to observe the changes in access times for each group under different capacity and demand levels, and how available capacity is utilized. We first test the impact of increasing the available care capacity by adding a new surgeon to the practice starting from 2020, and refer to this capacity scenario as *Scenario 1*. In the current simulated case, there are five surgeons with various FTE allocations to breast surgery. The new surgeon is modeled to have 95% of his/her FTE allocated to breast surgery. When simulating the future under Scenario 1, we assume that patient demand remains constant.

Under Scenario 1, we use the forecasted demand for each surgical group, obtained using an ARIMA model on the historical patient demand data.

Under *Scenario 2*, we test the impact of surgical complexity on access times. The care capacity modeled under Scenario 2 is similar to the one under Scenario 1, where a new surgeon is modeled to join the practice 2020 with 95% FTE allocated to breast surgery. In addition to this change in capacity, there is also a change in demand mix, increasing the demand for higher complexity cases while reducing the demand for lower complexity cases. Specifically, we test the case where the demand for groups 5, 6 and 7 are observed to be 2% above the forecasted demand while a reduction of demand from groups 1, 2, 3, and 4 are observed. Essentially, this results in same total demand volume as the forecasted total demand.

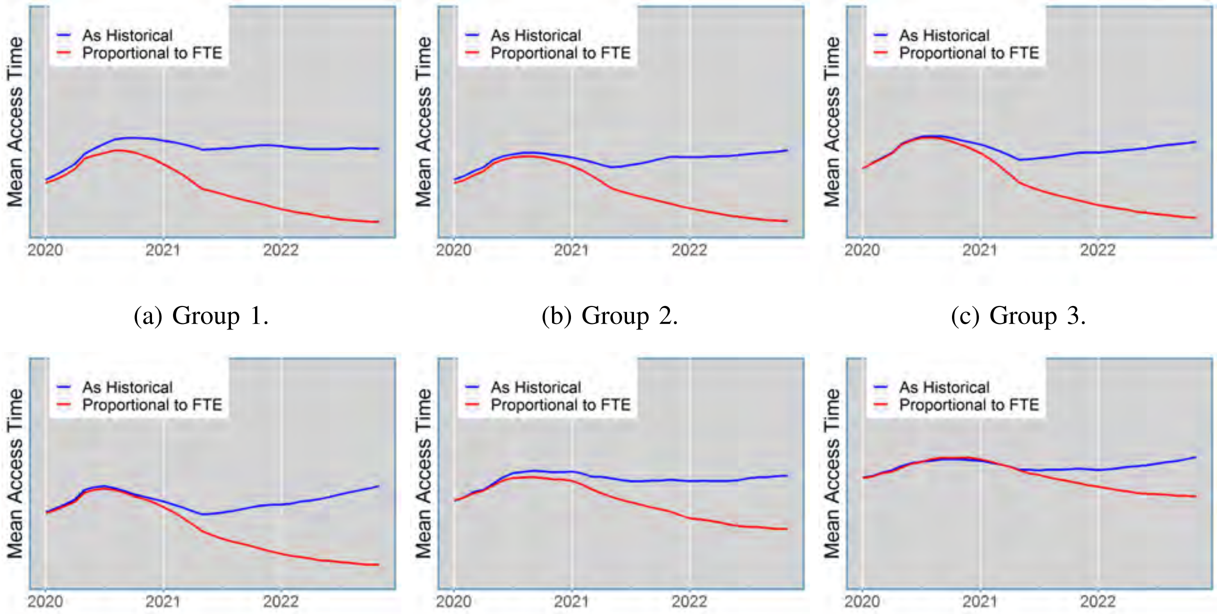
After identifying surgeon capacity and patient demand scenarios for simulating the future, we then identify possible case assignment strategies since it is critical to characterize how to utilize the capacity to observe the relationship between the available capacity and the patient access. In our case, we should also model the number of cases assigned to each surgeon as well as their complexity level, since once the patient is seen by a specific surgeon in clinic, it is not customary for this patient to be routed to another surgeon. Therefore, to be able to fully benefit from the available capacity, we need to avoid making a surgeon bottleneck by assigning too much of a workload either by case volume, case complexity, or the combination.To this end, we analyze different case assignment strategies to show additionally how different case assignments, both demand volume and complexity, can impact access time.

Under the first case assignment strategy (Strategy 1), we keep the case mix of the existing surgeons and their proportional workload the same while routing some of their workload to the newly hired surgeon. We reduce the workload of the five existing surgeons in equal proportion and route this portion of the demand to the new surgeon. In the second strategy (Strategy 2), we further analyze a case assignment strategy that assigns number of cases to the surgeons proportional to their FTE. Strategy 2 assigns cases to all the surgeons so that all have the same proportion of cases across the 6 groups. This case can be considered as balancing the utilization of the surgeons by assigning them demand proportional to their capacity.

5 RESULTS

Figures 6 and 7 show the the 12-month moving average of access times for the 2019-2022 period under these assumptions. The blue and red lines show the results under Strategy 1 and Strategy 2 case assignments, respectively. We remove the ticks on y-axis to mask the confidential access time information. The scales of each graph are the same to enable visual comparisons.

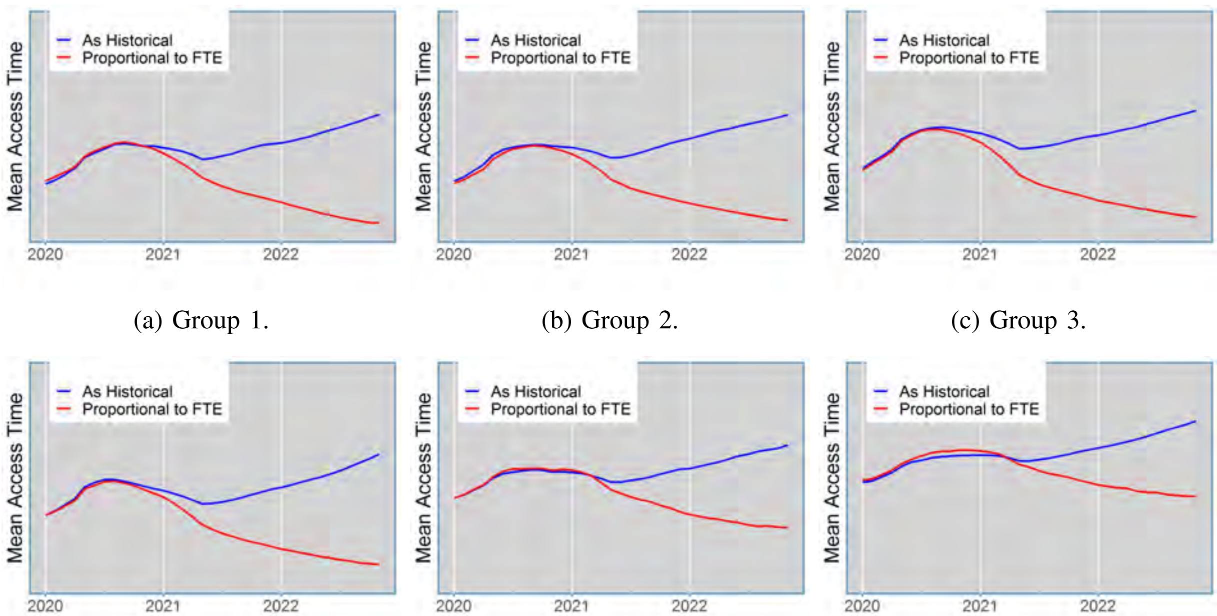
Due to the increase in capacity envisioned from the beginning of 2020, we observe a reduction in the access times for all patient groups. The reason why we are observing a lag in reduction in access times is due to the backlog of surgeries in the existing surgeons' calendars. Until this backlog is eliminated, all patients that are assigned to existing surgeons experience lengthy access delays. We report the difference between two scenarios as a proportion of the performance under Scenario 2, i.e., (Scenario 2-Scenario 1)/Scenario 2, and refer this as the *difference measure*. When we compare Scenario 1 and Scenario 2 by keeping the case assignment strategy the same, we observe that the difference in access times between the scenarios increases as the time progresses. For instance, for Group 2 under Strategy 1, the difference measure is 5% at the beginning of 2020, it becomes 16% and 22% at the beginning of 2021 and 2022, respectively. The same measures under Strategy 2 are 8%, 20%, and 30%. The difference measures calculated under Strategy 2 are typically higher since Strategy 2 better utilizes the available capacity and results in higher reduction in access times. Similar to the above comparison, we also contrast the performances of Strategy 1 and Strategy 2 under the same demand and capacity scenario. We again observe a greater difference between the performance measures under Strategy 1 and Strategy 2 as the time progresses. We observe a higher relative difference between the performances of two strategies under Scenario 2 compared to that observed under Scenario 1. The difference between the performance measures of Strategy 1 and Strategy 2 (Strategy 1-Strategy 2) is significantly higher under Scenario 2 compared to Scenario 1. When we calculate



(a) Group 1. (b) Group 2. (c) Group 3.

(d) Group 4. (e) Group 5. (f) Group 6.

Figure 6: Simulated access times with the planned changes under Scenario 1.



(a) Group 1. (b) Group 2. (c) Group 3.

(d) Group 4. (e) Group 5. (f) Group 6.

Figure 7: Simulated access times with the planned changes under Scenario 2.

at the ratio of the difference (Difference under Scenario 2/Difference under Scenario 1), we observe that for Groups 1 to 4, the ratio is 1.4 on average, it is 1.6 for Group 5, and 2 for Group 6.

Since Strategy 2 utilizes more of the capacity of newly hired surgeon and balances the workload among surgeons, it reduces bottlenecks and reduce the access times significantly. While case assignment Strategy 2 reduces the access times significantly, implementation of the strategy might not be realistic. Under Strategy 2, each surgeon is assigned the same portion of each surgical group, therefore, each surgeon's case mix is the same. Some surgeons might be specialized in certain surgical categories, therefore, they can prefer one surgical group to another in their practice. Strategy 2 improves the access times especially for the patients from Groups 1 to 4.

6 CONCLUSION

We present a simulation modeling framework to understand the relationship between the patient demand, available capacity, and resulting access times in a breast surgery practice. The results indicate that with the given available capacity, number of cases assigned to surgeons and the complexity case mix of this assigned demand can lead to significant changes in access times.

The simulation tool is flexible and easy to be used by the practice. The model is built as generic as possible to accommodate the future variations in capacity use and demand. It can be easily adjusted based on changes in number of surgeons and their FTEs as well as changes in case assignments which are the decision variables that the practice is focusing on. Additionally, the demand forecasts can easily be updated if significant changes are observed in arrival patterns as more data are collected.

6.1 Limitations and Challenges

In the validation of the simulation in Section 4.1, we make assumptions while calibrating the unobserved system parameters to bring our simulation results closer to reality. Certain parts of the patient flow is modeled as black boxes due to not having the data. For instance, the exact time spent by each surgeon on each case is not easy to observe from the data. It is clear that each surgeon spends at least the IC time for each case, however, we do not have accurate data on how much time spent on each case other than IC.

Another part of the patient flow that we model as a black box is the plastic surgeon calendars. For the cases that are grouped as Group 5 and Group 6, a plastic surgeon attendance is required and it results in additional delay for those patients. We do not have access to plastic surgeon calendars, therefore, we cannot search for an available slot at the time of assigning patient to breast surgeon calendar. We represent this detail in our model with probabilities of finding a plastic surgeon available on each week and calibrated those probabilities to reduce the discrepancies between the model results and results from historical data.

In our simulation model, the patient demand represents the patients that decided to have surgery whereas this decision is given after patient is seen by a surgeon in the clinic. Therefore, patient demand for surgery is bounded by the capacity in the clinic. Therefore, the demand case under Scenario 2 can be bounded by clinical availability. Additionally, due to shorter or longer access times patient demand for clinic can change since prolonged access times are associated with cancellation or no-show rates (see, e.g., Murray and Berwick (2003)). The impact of access time on patient demand is not straightforward to predict without making the actual change in the system.

6.2 Future Study

A possible direction for future study is expanding the patient flow that we model to include clinical appointments. The assignment strategies that we evaluated with our simulation model can only be possible if we assign these patients to surgeons' clinic appointments at the time of appointment request. One challenge in this assignment is determining the complexity group of arriving patient. At the time of surgical listing, the patient's complexity group of an arriving patient is apparent since the patient is already seen by the surgeon in the clinic. However, no such triage mechanism is available for the patient at the time of appointment request, and there will be limitations to any such attempts because patient decisions on procedures often change after meeting with the surgeon. Hence, one needs to first establish a pre-assessment scheme to identify patient complexity groups to achieve balanced patient mix among the surgeons and reduce the access times to surgery.

Another direction for future study is utilizing the existing simulation model to identify the required total FTE to reach the access targets that the practice sets forth. This increase in FTE can be possible by hiring new surgeons to the surgical practice. Simulation models can be used as tools to evaluate alternative scenarios to determine the required FTE allocated to the surgical practice for the new surgeon along with the possible case assignment to the new surgeon in terms of both total volume and case complexity mix.

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