Access To Colonoscopy Appointments

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CAPSULIZATION

• We present an integrated discrete event simulation tool.

• This approach helps us to study a variety of metrics associated with both scheduling and operations.

• Our goal is not to give specific recommendations but show how the integration of these stages is important to study the tradeoffs between different metrics.
OUTLINE

• Project Inspiration

• Simulation Details

• Analyses

• Results

• Conclusions

• Future Scope
INSPIRATION

• Colonoscopy is a kind of endoscopy; it is important because:

  • Colorectal cancer is the most common cause of cancer and is the second leading cause of cancer death in the US. [1]

  • Colonoscopy procedures have been shown to reduce the mortality rate by more than 50%. [2]
INSPIRATION

• Scheduling the patients for endoscopy clinics is both important and challenging as:

  • There are multiple sources of variability such as appointment demands, patient preferences, procedure durations, patient arrivals, provider arrivals and no shows.

  • Eventually we must make tradeoffs between patient and provider satisfaction, quality of care, patient access, staff overtime and clinic utilization.
PROBLEM STATEMENT

• How do we decide which scheduling policy works for a clinic?

• Quantifying the tradeoffs of different scheduling policies.

• Significance of base template for scheduling.

• How are metrics affected when scheduling and operations of clinic are observed as single set?
PREVIOUS WORKS

• The general focus in past has been either on scheduling or operations when building clinical simulation models – we took an integrated approach.

SCHEDULING:
• Scheduling Patients’ Appointments: Allocation of Healthcare Service (Chen et al., 2015) [3]
• A stochastic overbooking model for outpatient clinical scheduling with no-shows (Muthuraman & Lawley, 2008) [4]

OPERATIONS:
• A Discrete Event Simulation Model to evaluate operation performance of colonoscopy Suite (Berg et al., 2010) [5]
• Optimizing efficiency and operation at a California Safety-Net Endoscopy Center (Day et al., 2014) [6]
What is Discrete Event Simulation (DES) Model?
- Discrete event simulation (DES) is a method used to model real world systems that can be decomposed into a set of logically separate processes that autonomously progress through time.

Why DES?
- We wanted to model patients as an independent entities with associated attribute information,
- represent a real-life system with sufficient accuracy, and
- a method which is easily analytically tractable; DES does that.
FULL SIMULATION FLOW

Simulation starts

Is patient in arrival queue?

True → Patient calls

Is appointment available?

True → Schedule patient → Calculate Lead Time

False → Schedule finished

False → Unable to schedule

SCHEDULING

Is appointment still in schedule?

True → Patient arrives

True → Add wait time

Does patient arrive first?

True → Generate procedure time

Does procedure end after close?

True → Add overtime

False → False → Add idle time

provider arrives

Simulation ends
FEW DEFINITIONS

• Template:
  • It is building block of the schedule and is defined by the set of dates.
  • For each date, there is open and close time, set of appointment slots and set of candidate patient types for each appointment slot.
  • We have two types of patients: simple patients and complex patients.
A FEW DEFINITIONS

• Time Horizon:
  • The time duration for which the entire simulation is done.
  • In our case, it is six months.
  • We simulate the patients for the time horizon of six months and try to come up with the schedule for this period.

• Replication Size:
  • The sample size for the simulation i.e., the number of times we simulate the entire scenario, so that our results are statistically significant.
## ASSUMPTIONS & PARAMETERS

### Assumptions
- There is a single provider
- There are discrete groups of patient types
- Operations is considered as a single step

### Parameters
- 650 Replications
- 26 weeks (6 months)
- 2 patient types (simple and complex)
- Lag time of 5 days
REPLICATION/ SAMPLE SIZE

- Monte Carlo Approach
- We start with small sample size, i.e., 10 and recursively arrive at the required sample size.

\[ M_{\text{required}} > \left( \frac{2CS}{W} \right)^2 \]

- Where:
  - \( M_{\text{assumed}} \): initial sample size of replication,
  - \( A \): chosen metric (here it is lead time for complex patient),
  - \( \bar{A} \): mean of metric across the number of replications,
  - \( S \): standard deviation of the metric \( A \),
  - \( C \): \( z \) value at chosen confidence interval (95% in our case),
  - \( W \): standard error or width of confidence interval (0.5 days in our case),
  - \( M_{\text{required}} \): required sample size of the replication.
# Replication/ Sample Size

<table>
<thead>
<tr>
<th>$M_{\text{assumed}}$</th>
<th>$S$</th>
<th>$M_{\text{required (exact)}}$</th>
<th>$M_{\text{required (Rounded Up)}}$</th>
</tr>
</thead>
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<tr>
<td>10</td>
<td>3.16684</td>
<td>616.43</td>
<td>650</td>
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<td>100</td>
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<tr>
<td>1000</td>
<td>3.15707</td>
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<table>
<thead>
<tr>
<th>C</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.96</td>
<td>0.5</td>
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</table>
SAMPLE SCHEDULING POLICIES

**Case 1**

**Simple Template and Policy:** All appointments 45 minutes; first-available-appointment scheduling

**Case 2**

**Schedule by Patient Type:** 4:1 ratio of 40- and 60-minute appointments; first-available-appointment-by-type

**Case 3**

**Case 2 plus Patient Preferences:** Add in 25% likelihood for each morning/afternoon of patient unavailability
# SCHEDULE TEMPLATES

## Case 1 Template

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Appointment</th>
</tr>
</thead>
<tbody>
<tr>
<td>9:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>9:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>10:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>10:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>11:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>11:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>12:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>12:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>1:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>1:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>2:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>2:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>3:00</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>3:30</td>
<td>Appt Slot</td>
</tr>
<tr>
<td>4:00</td>
<td>Appt Slot</td>
</tr>
</tbody>
</table>

Appt Slot -> Simple/Complex

## Case 2 and 3 Template

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Appointment</th>
</tr>
</thead>
<tbody>
<tr>
<td>9:00</td>
<td>Type A</td>
</tr>
<tr>
<td>9:30</td>
<td>Type A</td>
</tr>
<tr>
<td>10:00</td>
<td>Type A</td>
</tr>
<tr>
<td>10:30</td>
<td>Type A</td>
</tr>
<tr>
<td>11:00</td>
<td>Type A</td>
</tr>
<tr>
<td>11:30</td>
<td>Type A</td>
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<tr>
<td>12:00</td>
<td>Type B</td>
</tr>
<tr>
<td>12:30</td>
<td>Type B</td>
</tr>
<tr>
<td>1:00</td>
<td>Type A</td>
</tr>
<tr>
<td>1:30</td>
<td>Type A</td>
</tr>
<tr>
<td>2:00</td>
<td>Type A</td>
</tr>
<tr>
<td>2:30</td>
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<tr>
<td>3:00</td>
<td>Type A</td>
</tr>
<tr>
<td>3:30</td>
<td>Type B</td>
</tr>
<tr>
<td>4:00</td>
<td>Type B</td>
</tr>
</tbody>
</table>

Type A -> Simple  
Type B -> Complex
SCHEDULING FLOW SIMULATION

Patient Calls for Appointment

Is Appointment Available? – variability in availability

Patient is Scheduled
SIMULATING SCHEDULE CONSTRUCTION

<table>
<thead>
<tr>
<th>Value</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Patient</td>
<td>SP</td>
</tr>
<tr>
<td>Complex Patient</td>
<td>CP</td>
</tr>
</tbody>
</table>
OPERATIONS FLOW SIMULATION

Patient Arrives at Clinic – Variability in arrival

Procedure duration is generated – Variability in duration and prep

Patient Exits the Clinic
METRICS

- Average Lead Time
- Patient Wait Time
- Patient Preferences
- Provider Idle Time
- Provider Overtime
# RESULTS – TYPICAL CLINIC VS. NEW POLICY

Change in Key Metrics from Case 1 (Typical Clinic) to Case 2 (New Policy)

<table>
<thead>
<tr>
<th>Case</th>
<th>Lead Time per Simple Patient (Days)</th>
<th>Lead Time per Complex Patient (Days)</th>
<th>Wait Time per Patient (Min)</th>
<th>Provider Overtime per Day (Min)</th>
<th>Provider Idle Time per Day (Min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>6.781</td>
<td>6.783</td>
<td>7.974</td>
<td>12.506</td>
<td>46.185</td>
</tr>
<tr>
<td>Case 2</td>
<td>6.395</td>
<td>11.925</td>
<td>2.683</td>
<td>2.578</td>
<td>44.334</td>
</tr>
<tr>
<td>% Change</td>
<td>-5.7 %</td>
<td>+75.80 %</td>
<td>-66.38 %</td>
<td>-79.37 %</td>
<td>-4 %</td>
</tr>
</tbody>
</table>
## RESULTS – NEW POLICY VS. NEW POLICY WITH PREFERENCE

Change in Key Metrics from Case 2 (New Policy) to Case 3 (New Policy with Preference)

<table>
<thead>
<tr>
<th>Case</th>
<th>Lead Time per Simple Patient (Days)</th>
<th>Lead Time per Complex Patient (Days)</th>
<th>Wait Time per Patient (Min)</th>
<th>Provider Overtime per Day (Min)</th>
<th>Provider Idle Time per Day (Min)</th>
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<td>11.925</td>
<td>2.683</td>
<td>2.578</td>
<td>44.334</td>
</tr>
<tr>
<td>Case 3</td>
<td>6.596</td>
<td>12.028</td>
<td>2.672</td>
<td>2.558</td>
<td>44.238</td>
</tr>
<tr>
<td>Change (2 v 3)</td>
<td>+3.15 %</td>
<td>+0.86 %</td>
<td>-0.42 %</td>
<td>-0.80 %</td>
<td>-0.22 %</td>
</tr>
</tbody>
</table>
TAKEAWAYS FROM RESULTS

• By-type scheduling policy greatly reduces the patient wait time, provider idle and overtime. However:
  • It increases the lead time for complex patients, while decreases for simple patients
  • We attribute this to number of slots available per day for each patient type.

• Lead time and Base template are the two important factors in determining the schedule.

• Patient preferences does not have a significant impact on most of the metrics
CONCLUSION

• Our integrated simulation tool allows new policies to be tested robustly at low cost.

• We were able to test basic policies against new policies and analyze tradeoffs between important clinic metrics:
  • Pros and Cons of the proposed policies depend on the tradeoffs that we are willing to make,
  • For an instance, if we want lower lead time for complex patients, then we should prefer simple first come first serve policy, but then again this will be at expense of higher wait time for patients in general.
FUTURE SCOPE

• Enhance the current model to account for more variability.

• Adding multiple providers.

• Expand our appointment operations to include multiple stages (e.g., intake, procedure, recovery).
ACKNOWLEDGEMENTS

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QUESTIONS?

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OR
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REFERENCES


DETAILED RESULTS

• We attribute this to the policy difference in scheduling for both cases; in Case 1 we have first come first serve basis so any patient can get any slot, hence, giving every patient equal preference. However, in Case 2 the complex patients are scheduled only twice a day, thus fewer slots are available to them and hence the higher lead time. This result is quantitatively supported by the fact that in both Case 1 and 2, we have 46,800 minutes and 41,600 minutes, respectively, allocated for simple patients. In both cases we have 1020 and 1019 simple patient arrivals and hence scheduling them will need 45,900 minutes and 40,760 minutes, respectively. Thus, we have more time allocated to simple patients than required. While the case is opposite for complex patients, we have 283 patients in both cases with 11,700 minutes and 15,600 minutes allocated. However, scheduling 283 patients requires 12,735 minutes and 16,980 minutes, respectively. Also, in Case 2, the time allotted is short by 1380 minutes (note that Case 2 has 60 minutes for every complex patient as opposed to 45 minutes in Case 1) while case 1 is short by 1035 minutes, thereby Case 2 has a higher lead time for complex patients.

• Moving from Case 2 to 3, we see about 3.15% and 0.86% increase in the average lead time for simple and complex patients, respectively. This increase is due to the preferential appointment selection by simple patients.