IISE ANNUAL Virtual CONFERENCE & EXPO 2020

Access To Colonoscopy Appointments

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CHEPS

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Rx

A prescription to address system complexity in healthcare

INNOVATING HEALTHCARE DELIVERY

FOSTERING LEARNING

BUILDING COMMUNITY

POSITIVE IMPACT THROUGH...

Research
Education
Implementation
Outreach
Dissemination

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:

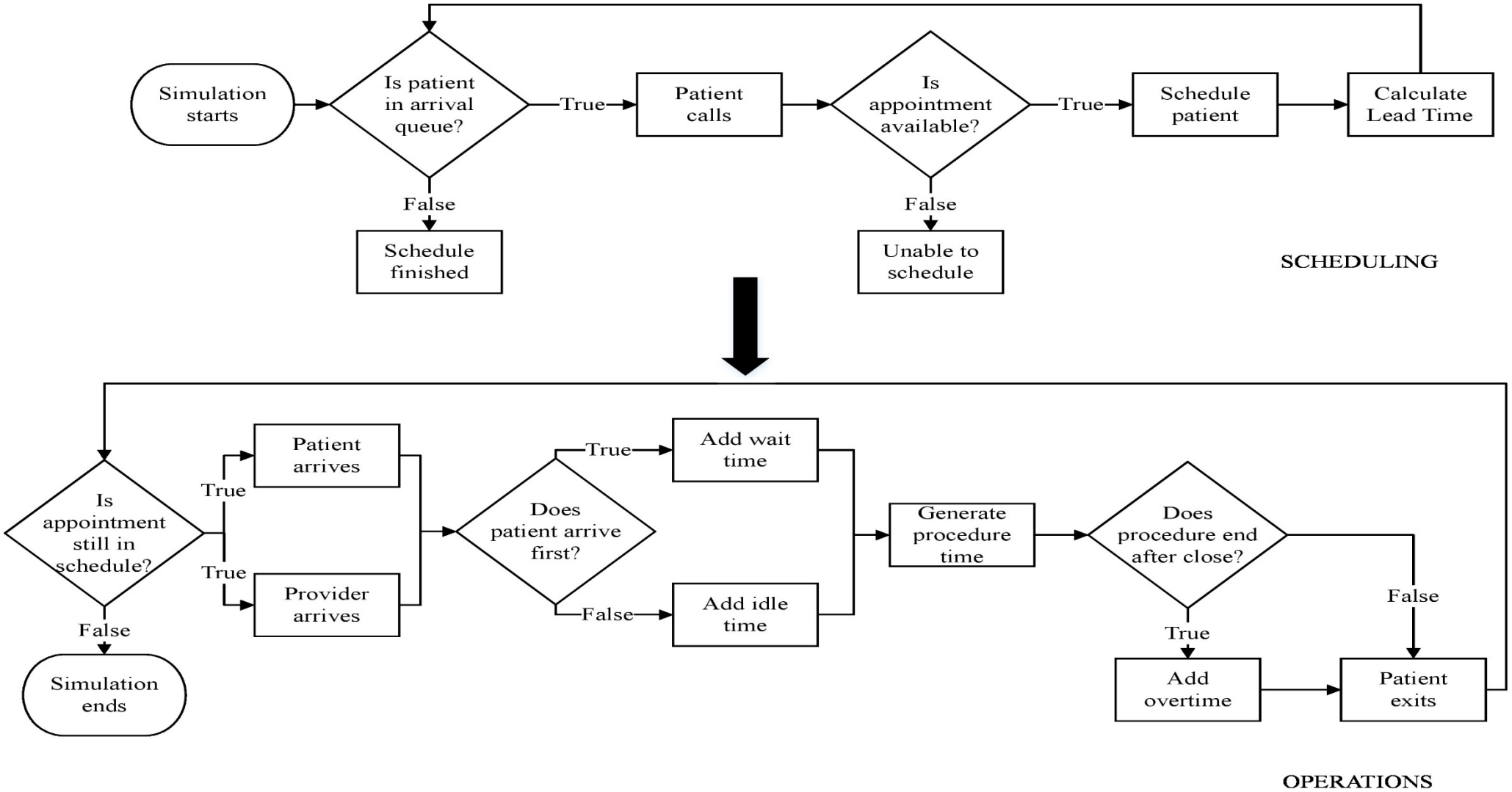
- A Discrete Event Simulation Model to evaluate operation performance of colonoscopy Suite (Berg et al., 2010) [5]
- Optimizing efficiency and operation at a California Safety-Net Endoscopy Center (Day et al., 2014) [6]

DISCRETE EVENT SIMULATION

- 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.

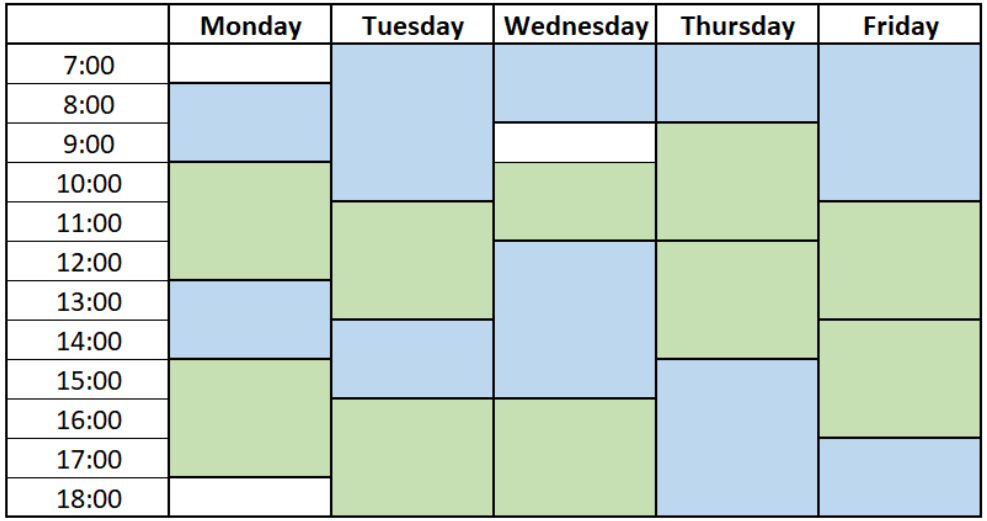
- Why DES?
  - We wanted to model patients as an independent entities with associated attribute information,
  - represent a real-life system with sufficient accuracy, and
  - a method which is easily analytically tractable; DES does that.

FULL SIMULATION FLOW



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.



VALUE	ABBREVIATION
Simple Patient	SP
Complex Patient	CP

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	Parameters
• There is a single provider • There are discrete groups of patient types • Operations is considered as a single step	• 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.

$$M_{required} > \left\lceil \left(\frac{2CS}{W} \right)^2 \right\rceil$$

- Where:
  - $M_{assumed}$: 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),
  - $M_{required}$: required sample size of the replication.

REPLICATION/ SAMPLE SIZE

$M_{assumed}$	S	$M_{required}$ (exact)	$M_{required}$ (Rounded Up)
10	3.16684	616.43	650
100	3.16136	614.29	650
200	3.13605	604.50	650
400	3.25000	649.23	650
600	3.15150	610.47	650
800	3.10350	592.03	650
1000	3.15707	612.23	650

c	w
1.96	0.5

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

Appt Slot -> Simple/ Complex

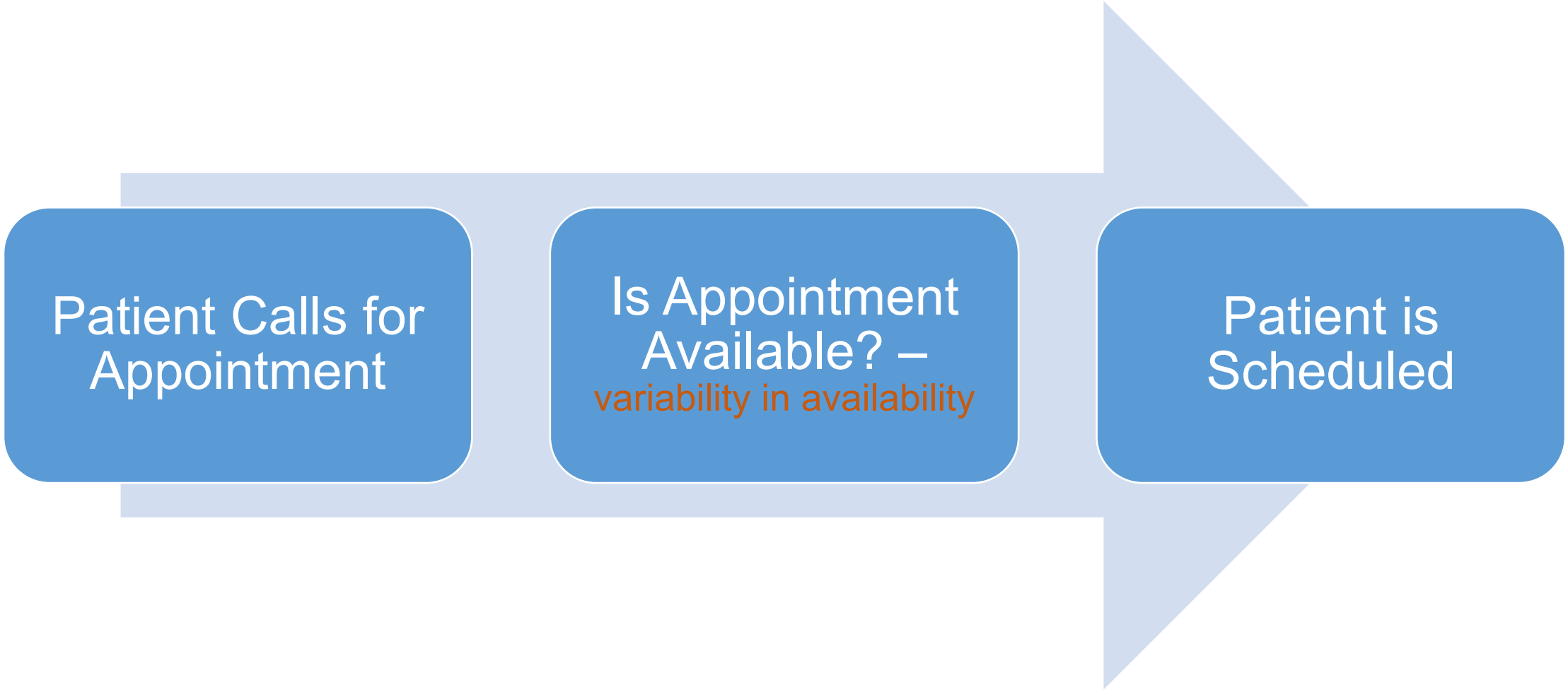
Time of Day	Appointment
9:00	Appt Slot
9:30	Appt Slot
10:00	Appt Slot
10:30	Appt Slot
11:00	Appt Slot
11:30	Appt Slot
12:00	Appt Slot
12:30	Appt Slot
1:00	Appt Slot
1:30	Appt Slot
2:00	Appt Slot
2:30	Appt Slot
3:00	Appt Slot
3:30	Appt Slot
4:00	Appt Slot

Case 2 and 3 Template

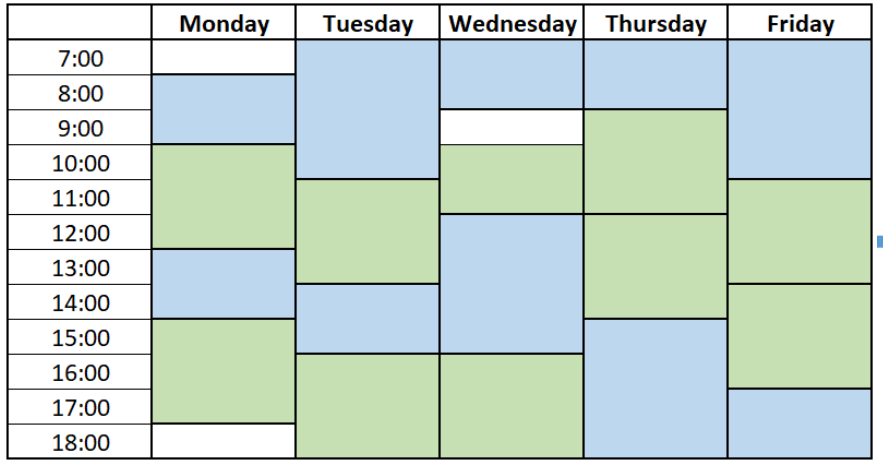
Type A -> Simple	Type B -> Complex

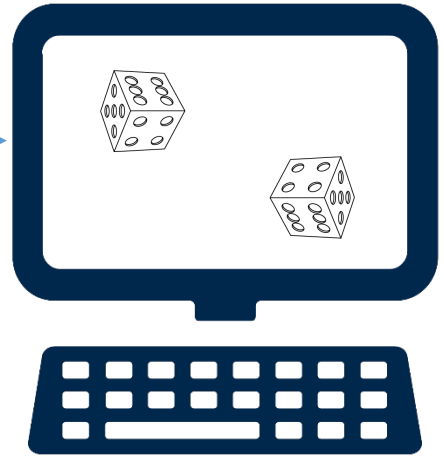
Time of Day	Appointment
9:00	Type A
9:30	Type A
10:00	Type A
10:30	Type A
11:00	Type A
11:30	Type B
12:00	Type B
12:30	Type A
1:00	Type A
1:30	Type A
2:00	Type A
2:30	Type A
3:00	Type A
3:30	Type B
4:00	Type B

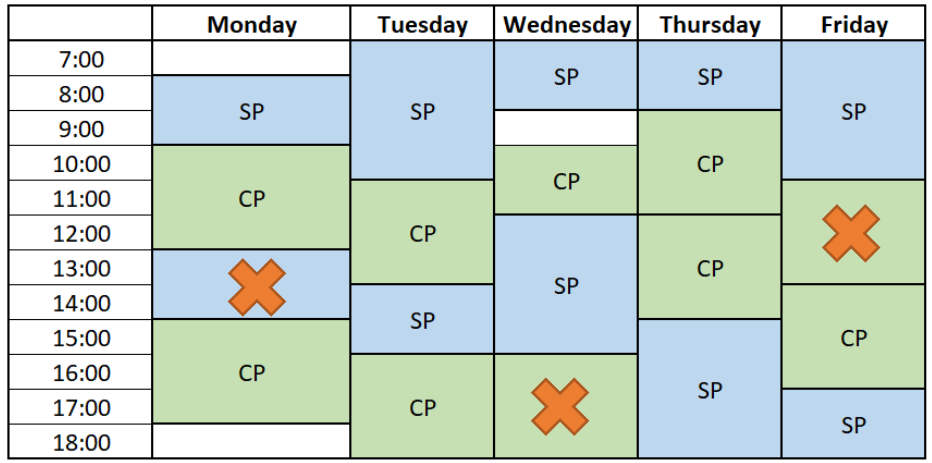
SCHEDULING FLOW SIMULATION

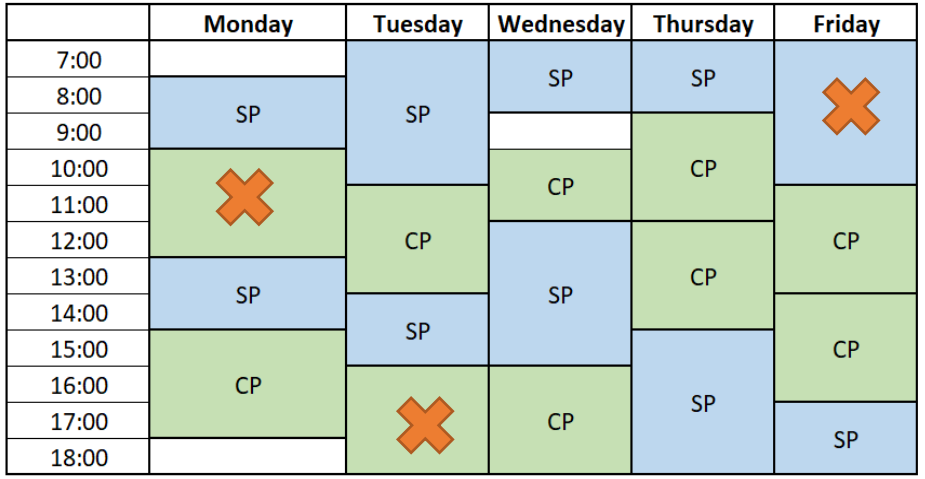


SIMULATING SCHEDULE CONSTRUCTION









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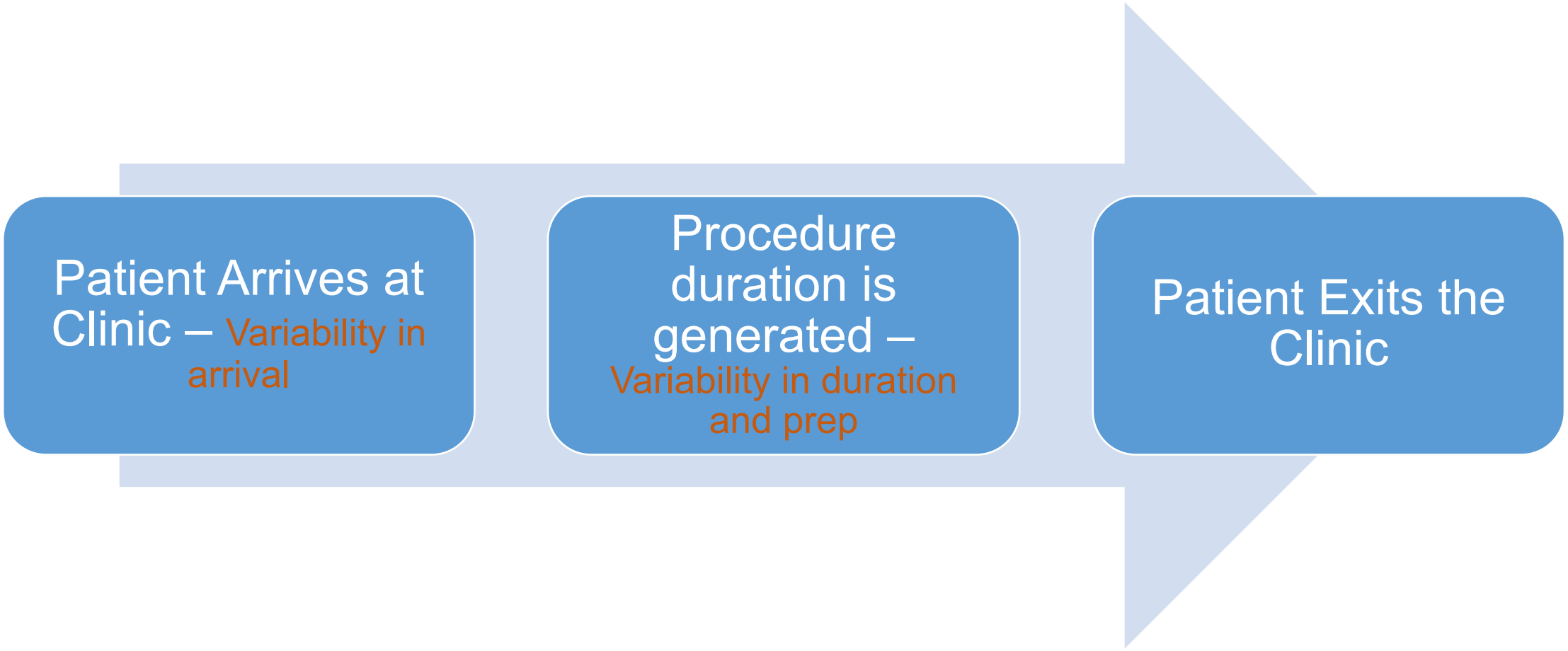
OPERATIONS FLOW SIMULATION



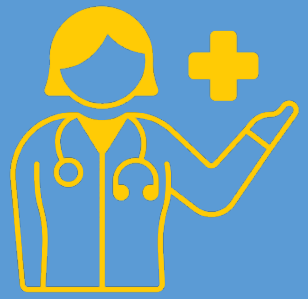
METRICS

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)

Case	Lead Time per Simple Patient (Days)	Lead Time per Complex Patient (Days)	Wait Time per Patient (Min)	Provider Overtime per Day (Min)	Provider Idle Time per Day (Min)
Case 1	6.781	6.783	7.974	12.506	46.185
Case 2	6.395	11.925	2.683	2.578	44.334
% Change	**-5.7 %**	**+75.80 %**	**-66.38 %**	**-79.37 %**	**-4 %**

RESULTS – NEW POLICY VS. NEW POLICY WITH PREFERENCE

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

Case	Lead Time per Simple Patient (Days)	Lead Time per Complex Patient (Days)	Wait Time per Patient (Min)	Provider Overtime per Day (Min)	Provider Idle Time per Day (Min)
Case 1	6.781	6.783	7.974	12.506	46.185
Case 2	6.395	11.925	2.683	2.578	44.334
Case 3	6.596	12.028	2.672	2.558	44.238
Change (2 v 3)	**+3.15 %**	**+0.86 %**	**-0.42 %**	**-0.80 %**	**-0.22 %**

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).

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QUESTIONS?

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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.