Surgery Scheduling: Research and Practice

Scheduling Seminar Series
June 7, 2023

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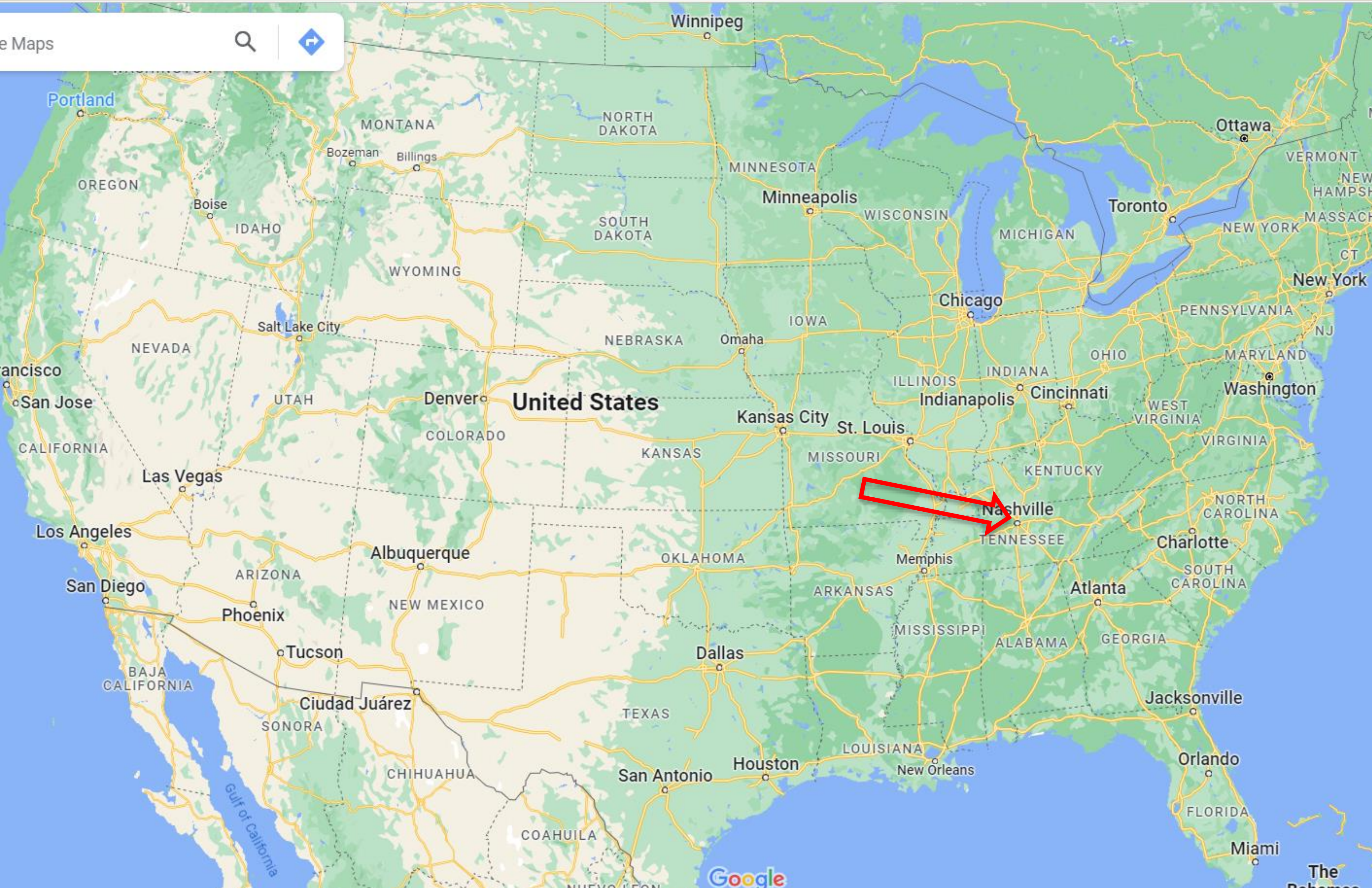
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Vanderbilt University Medical Center

Vanderbilt Health is a growing health system, anchored by Vanderbilt University Medical Center. We are one of the largest and most prominent academic medical centers in the Southeast, with seven hospitals and more than 200 clinics across Tennessee and in neighboring states.

THE FACTS

1,709 licensed beds across seven hospitals

- Vanderbilt University Hospital
- Monroe Carell Jr. Children's Hospital at Vanderbilt
- Vanderbilt Psychiatric Hospital
- Vanderbilt Stallworth Rehabilitation Hospital
- Vanderbilt Wilson County Hospital
- Vanderbilt Bedford Hospital
- Vanderbilt Tullahoma-Harton Hospital

4 on-campus surgical sites (58 ORs) + 2 ambulatory sites (11 ORs)

Nearly 3 million patient visits*

Over 88,000 surgical cases*

55,000+ surgical cases / year

75,000 hospital discharges*

Over 161,000 emergency department visits*

$4.7 billion net patient services revenue**

Nearly 40,000 employees*

Nearly 2,000 Vanderbilt Medical Group employed physicians*

More than 1,000 resident physicians each year*

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Objective of this talk

- Familiarize the audience with processes around management of OR capacity, as well as surgical scheduling.
- Discuss 1 or 2 of my recently published research alongside my coauthors.
- Discuss a couple of unexplored research topics in surgery/OR scheduling.

What is an Operating Room? What is Surgery?

Circulator (Nurse)

Surgeon

Patient

Scrub Tech (Nurse)

Ambulatory ORs vs Non-Amb. ORs

- Ambulatory Surgical Centers (ASC):
  - Outpatient surgeries (i.e., same day discharge)
    - Home → HR/prep → OR → PACU/recovery → Home
    - Smaller surgery durations, less acuity, faster recovery, shorter OR block time (typically 8-10 hours), faster turnaround time between cases
    - Could be single specialty or multi-specialty
      - Eye, GYN, Orthopedics, Urology, Dentistry, Plastics, Pediatric (Otolaryngology)

Ambulatory ORs vs Non-Amb. ORs

- Non-ambulatory ORs (“main ORs”):
  - Oriented towards inpatient surgeries but can (and often) also do Outpatient procedures
    - Home → HR/prep → OR → PACU/recovery → Home
    - Home → HR/prep → OR → ICU→ Unit → Home
    - Unit → OR →……
    - ED → OR →
  - Specialized ORs, not complete flexibility w.r.t. case placement (e.g., cardiac surgery, pulmonary, vascular surgery, etc.)

Disclaimers

– My views are influenced by large level-1 trauma academic medical centers in the US
– Not-for-profit center
– There are many similarities in scheduling surgeries and capacity management of ORs with for-profit, community hospitals, govt. hospitals, etc., but also differences
– Surgery scheduling processes likely differ between countries as well

How do surgeries get scheduled?

- Electively scheduled surgery
  - Primacy care refers patient to surgical clinic or patient searches for surgeon of repute; schedules appointment; at the visit, surgeon determines if surgery needed; books surgical appointment for a future date on which surgeon will be in the OR and has unfilled capacity in his/her “block”, and the time day/time also works for the patient
- Emergency surgery
  - Patient comes to the ER/ED → OR

Electively Scheduled Surgeries

- Two concepts from previous slide:
  - Surgery schedule (for a surgeon) for a future day builds up slowly, and is likely going to be fixed (i.e., the surgeon doesn’t usually move the case to a different day)
  - Block time used to allocate OR capacity

Elective Schedule Builds over time

/s)

			Days Out																													
eek	Date	Actuals*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	Thu 06/01	**49**	49	49	47	47	47	47	48	43	41	39	36	36	36	34	32	31	29	29	29	29	28	26	25	25	25	25	25	24	24	23
	Fri 06/02	**36**	34	35	32	31	31	31	31	30	29	29	28	28	28	28	25	25	24	21	20	20	20	19	18	18	14	13	13	13	13	13
2	Mon 06/05		49	48	48	48	47	45	45	45	45	45	45	46	45	44	44	44	44	43	43	41	41	40	40	40	38	37	37	36	34	34
	Tue 06/06			57	57	57	57	54	54	52	52	52	52	51	50	49	48	46	46	46	45	45	44	41	39	39	39	37	32	31	30	29
	Wed 06/07				41	41	41	41	38	37	37	37	37	37	36	34	31	30	29	29	29	27	25	24	24	21	21	21	20	19	18	17
	Thu 06/08					41	41	41	40	39	37	34	34	34	34	34	32	30	30	28	28	28	26	26	25	24	24	24	24	22	22	22
	Fri 06/09						28	28	28	27	27	27	27	27	27	27	27	25	25	25	25	25	25	24	23	22	22	22	22	22	21	18
3	Mon 06/12									48	48	48	48	49	50	49	49	49	49	47	45	44	43	42	42	42	41	41	37	36	35	35
	Tue 06/13										48	48	48	47	44	43	43	43	43	43	43	42	42	40	37	37	37	36	33	31	30	30
	Wed 06/14											44	44	44	42	41	40	38	38	38	38	38	36	36	34	34	34	34	34	33	32	31
	Thu 06/15												40	40	40	40	38	37	37	37	37	37	37	35	34	33	33	33	33	31	31	29
	Fri 06/16													27	27	27	24	22	18	18	18	18	18	18	18	18	17	16	16	16	14	14
4	Mon 06/19																37	37	37	37	37	37	36	36	36	36	35	35	35	33	33	33
	Tue 06/20																	43	43	43	42	41	39	38	38	38	38	38	38	37	35	32
	Wed 06/21																		35	35	35	31	31	28	27	27	27	27	26	26	25	25
	Thu 06/22																			27	27	27	27	24	24	22	22	22	22	22	19	16
	Fri 06/23																				21	21	21	20	18	18	16	16	16	16	16	15
5	Mon 06/26																							38	38	38	36	35	34	33	33	33
	Tue 06/27																								25	25	25	24	24	22	23	23
	Wed 06/28																									24	24	24	24	23	23	21
	Thu 06/29																										26	26	26	25	24	24
	Fri 06/30																											23	23	23	22	21
6	Mon 07/03																														17	17

Education | July 2014

Predicting Case Volume from the Accumulating Elective Operating Room Schedule Facilitates Staffing Improvements

Vikram Tiwari, Ph.D.; William R. Furman, M.D.; Warren S. Sandberg, M.D., Ph.D.

+ Author and Article Information

Anesthesiology July 2014, Vol. 121, 171–183.
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DECISION SCIENCES
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Predicting Daily Surgical Volumes Using Probabilistic Estimates of Providers' Future Availability

Online Bin-Packing Problem

- Variant of block scheduling used in community hospitals – online bin-packing problem, as surgeries arrive one at a time
  - Bandi & Gupta (2020, M&SOM): Operating Room Staffing and Scheduling
  - Hospital exercises control over blocks; surgeon operates in any OR that block gets assigned to; schedules develop 2-3 days in advance; cases that don't fit the scheduled time are deferred to future days

Need for Differential Scheduling / Capacity Allocation Policies

Cluster Num	Cluster Membership	TMinus0_1	TMinus2_7	TMinus8_14	TMinus15_28	TMinus29+	Case Vol Combined	Cluster Name
1	1	16%	46%	18%	14%	6%	162	
2	1	0%	3%	6%	46%	44%	95	
3	65	60%	19%	8%	8%	5%	7644	**Exclusively Add-Ons Cluster**
4	108	15%	18%	18%	25%	24%	20233	**50% Prior to T-15**
5	68	6%	6%	10%	19%	60%	13221	**Exclusively Electives**

Electively Scheduled Surgeries

- Two concepts from previous slide:
  - Surgery schedule (for a surgeon) for a future day builds up slowly, and is likely going to be fixed (i.e., the surgeon doesn't usually move the case to a different day)
  - Block time used to allocate OR capacity

Block Scheduling - Service

Rooms	Monday	Tuesday	Wednesday	Thursday	Friday
RM 01	Neuro Interventional 0730 - 1530	Neuro Interventional 0730 - 1530	Neuro Interventional 0800 - 1600	Neuro Interventional 0730 - 1530	Neuro Interventional <u>Week 1</u> 0900 - 1600 <u>Week 2,3,4,5</u> 0800 - 1600
RM 02	Urology Surgery 0730 - 1730	Urology Surgery 0730 - 1730	Urology Surgery 0800 - 1800	Urology Surgery 0730 - 1730	Urology Surgery <u>Week 1</u> 0900 - 1800 <u>Week 2,3,4,5</u> 0800 - 1800
RM 03	Neurosurgery 0730 - 1730	Neurosurgery 0730 - 1730	General Oncology Surgery 0800 - 1800	Thoracic <u>Week 1,3,5</u> 0730 - 1230 <u>Week 2,4</u> 0730 - 1730	Urology Surgery <u>Week 1</u> 0900 - 1800 <u>Week 2,3,4,5</u> 0800 - 1800
RM 04	Urology Surgery 0730 - 1930	Thoracic 0730 - 1930	Urology Surgery 0800 - 1800	Thoracic 0730 - 1930	Thoracic <u>Week 1</u> 0900 - 1800 <u>Week 2,3,4,5</u> 0800 - 1800
RM 05	Cardiac 0730 - 1930	Cardiac 0730 - 1930	Cardiac 0800 - 2000	Cardiac 0730 - 1930	Cardiac <u>Week 1</u> 0900 - 2000 <u>Week 2,3,4,5</u> 0800 - 2000

Block Scheduling – Surgeon / Service

Rooms	Monday	Tuesday	Wednesday	Thursday	Friday
ASC OR 01		Week 1,2,3 0700 - 1700 , MD	0700 - 1700 MD	Week 1,3 0700 - 1200 MD	Week 1,3 0700 - 1700 Ophthalmology Week 4 0700 - 1200 MD
ASC OR 02	Week 1,3 0700 - 1200 MD Week 2,4 0700 - 1200 Br MD 1200 - 17 DO	Week 1,3 0700 - 1200 , MD Week 2 0730 - 1200 , MD 1200 - 170 E , MD	Week 1 1200 - 1700 , MD Week 1,3 0700 - 1200 , MD Week 2,4 0700 - 1700 Community Otolaryngology Week 3 1300 - 1700 , MD	Week 2 0700 - 1700 Community Otolaryngology Week 3 1200 - 1700 MD Week 4 0700 - 1200 MD	Week 1,3 1200 - 1700 , DO Week 2 0700 - 12 MD Week 4 0700 - 1700 MD

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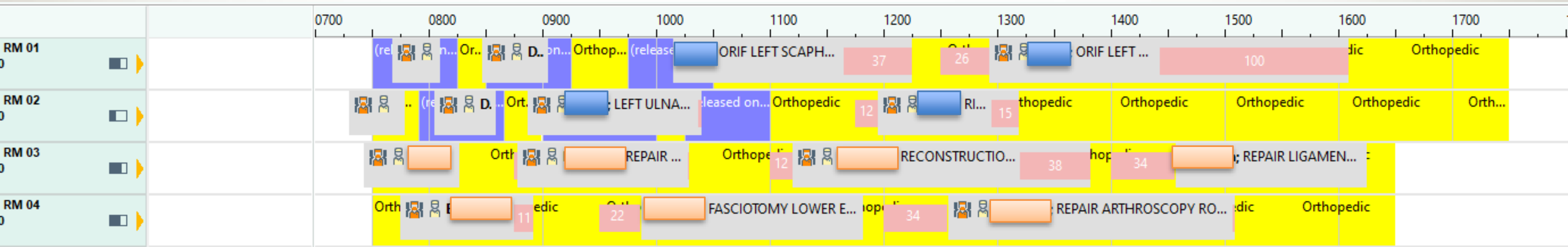
OR Capacity Management

- Hopp & Lovejoy (2014, Chapter 4): Hospital Operations: Principles of High Efficiency Health Care
- Strategic: How many ORs (and pre-op and post-op bays) to plan
  - Youn S, Geismar HN, Sriskandarajah C, Tiwari V. Adaptive Capacity Planning for Ambulatory Surgery Centers. *Manufacturing & Service Operations Management*. 2022 Nov;24(6):3135-57.
- Tactical: How many ORs to allocate to which surgeon/service on which days of the week; how many days in advance should capacity be released, etc.; how to measure ASC capacity util. vs. "main OR"
- Operational: <24 hours from day-of-surgery, for example, how to fit add-on cases?

Several Excellent Review Articles

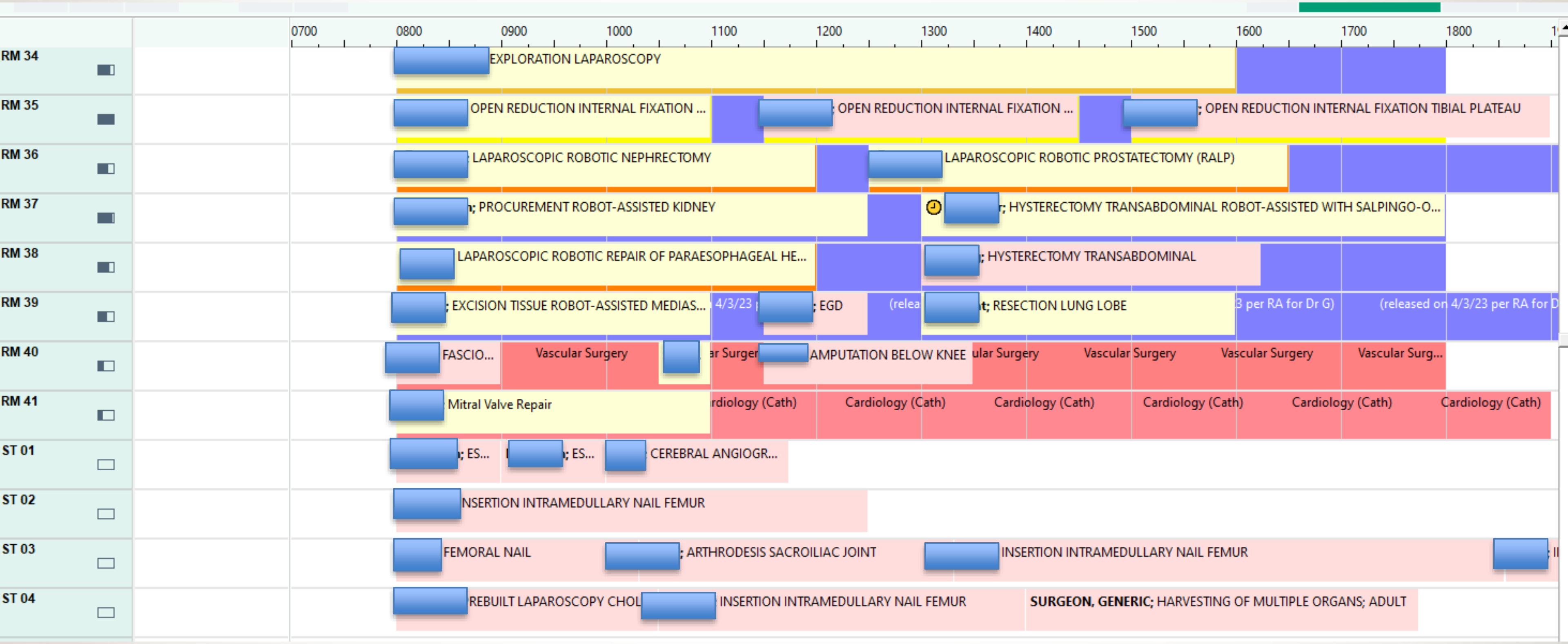
- Samudra M, Van Riet C, Demeulemeester E, Cardoen B, Vansteenkiste N, Rademakers FE. Scheduling operating rooms: achievements, challenges and pitfalls. *Journal of scheduling*. 2016 Oct;19:493-525.
- Youn S, Geismar HN, Pinedo M. Planning and scheduling in healthcare for better care coordination: Current understanding, trending topics, and future opportunities. *Production and Operations Management.* 2022 Dec;31(12):4407-23.

Actual Day of Surgery at an ASC



Example of an ASC center. 2 surgeons over 4 ORs. One surgeon did 8 short cases; other surgeon did 6 cases

Schedule at the Main OR at T-1



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Scheduling Elective Surgeries with Emergency Patients at Shared Operating Rooms

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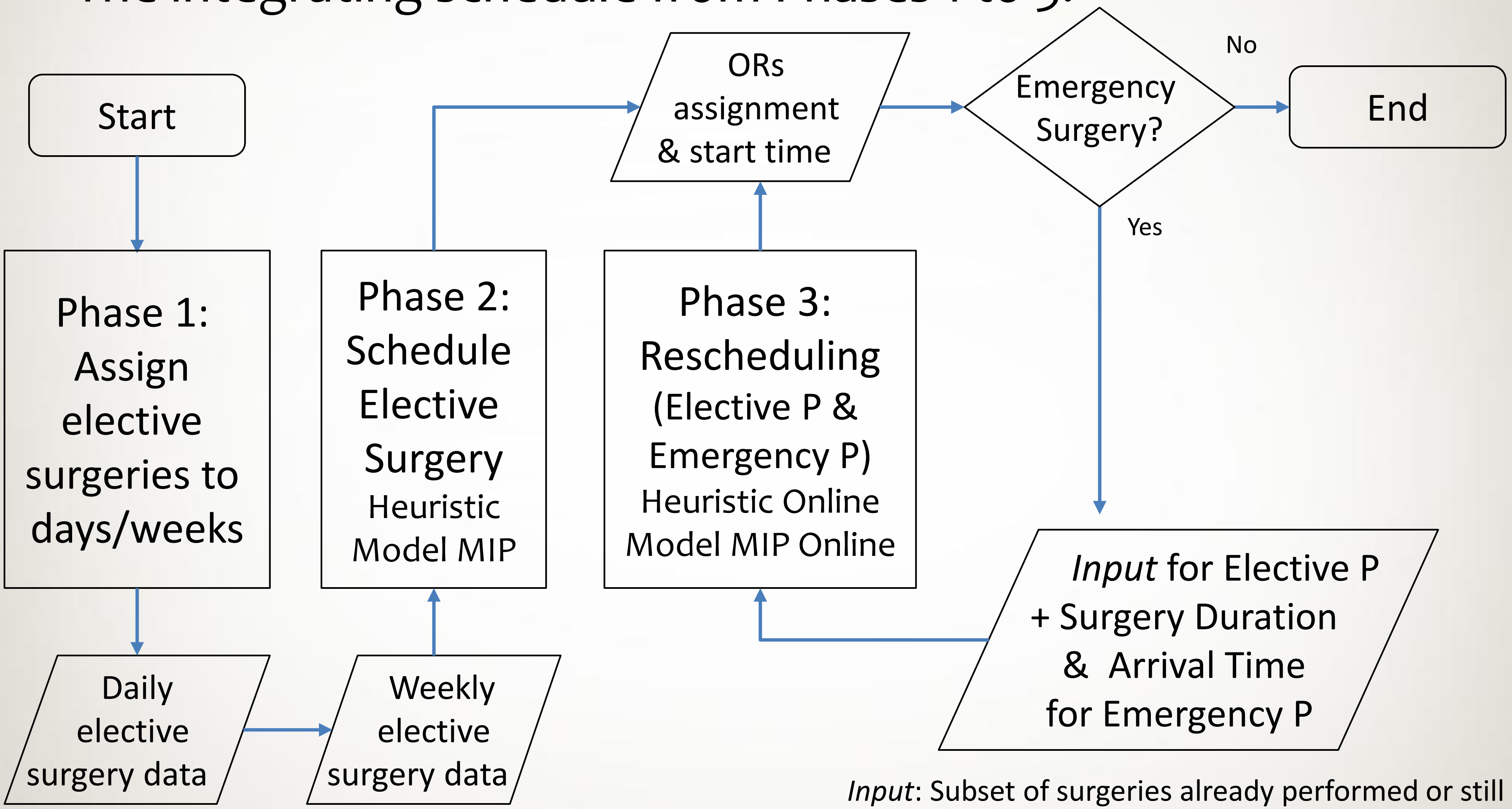
Dedicated or Flexible ORs for Emergency Surgeries?

- Dedicated OR: leave OR(s) open for unscheduled surgeries
- Flexible OR: don’t leave ORs open, but just “fit” emergency cases as they come in the already scheduled ORs with elective cases
- Partially flexible ORs: mix of the above

Process

- The integrating schedule from Phases 1 to 3.



Input: Subset of surgeries already performed or still being performed

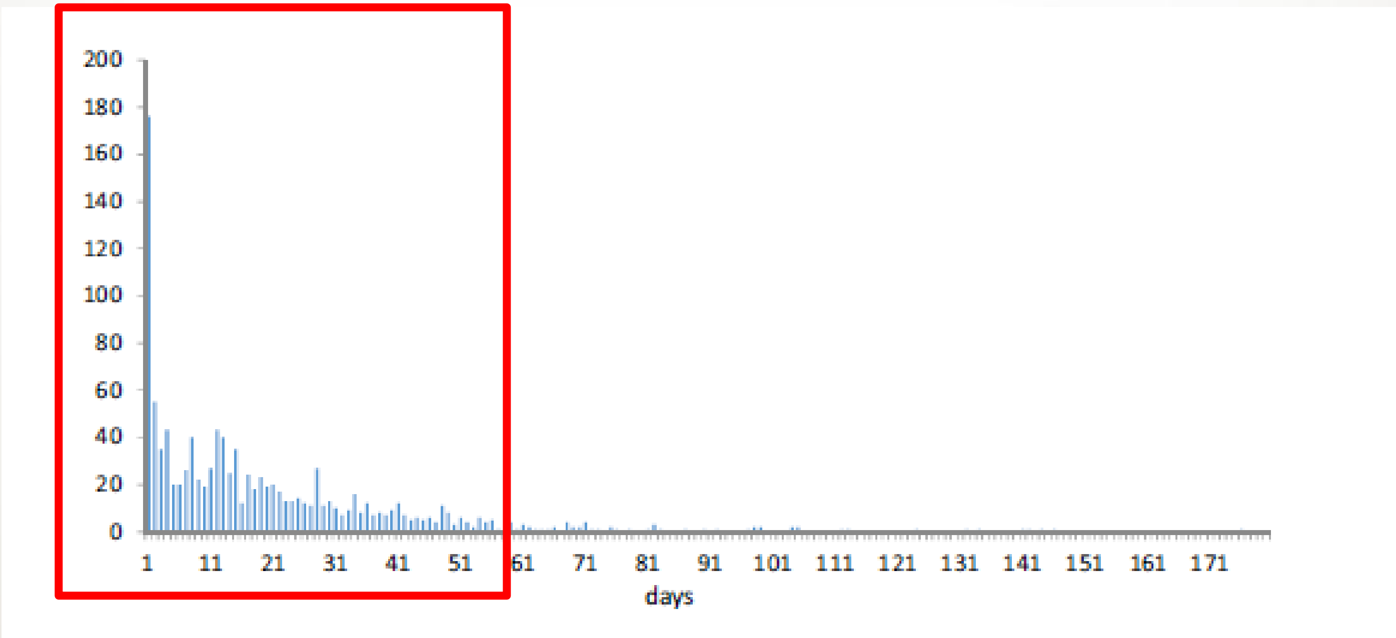
Number of Patients (Best Combination)

General Information

- Three Special ORs (namely OR1, OR2, and OR3) out of 39 ORs
  - Trauma case related to neurosurgery.
- Weekly block schedule (five days per week), 10 hours/day
- Daily schedule with **some capacities** for emergency patients.
  - Any arrival of emergency patients should be accommodated in an OR with 2 hours of its arrival.
- The surgery preparation: 30 minutes.

[Phase 1] Elective Patients

- Aggregate date from October 1, 2014 through July 31, 2015
- In total, 1121 elective patients to be scheduled
- 952 elective patients are scheduled within two months



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[Phase 1] Aggregate Schedule For Elective Patients

- Three types of surgeries
  - Type A (P >= 6); Type B (2 < P < 6); Type C (P <=2)
- Daily Schedule Pattern

Table 5 Daily Schedule Patterns

Daily pattern	OR_1	OR_2 or OR_3	Approximately total hour
1	Few Type C	Type A : 8.0 hours	23 hours
2	Few Type C	Type A : 7.5 hours	23 hours
3	Few Type C	Type A : 7.0 hours	23 hours
4	Few Type C	Type A : 6.5 hours	23 hours
5	Few Type C	Type A : 6.0 hours, Type C : 1.0 hours	23 hours
6	Few Type C	Type B : 5.5 hours, Type C : 1.5 hours	23 hours
7	Few Type C	Type B : 5.5 hours, Type C : 1.0 hours	23 hours
8	Few Type C	Type B : 5.0 hours, Type C : 2.0 hours	23 hours
9	Few Type C	Type B : 5.0 hours, Type C : 1.5 hours	23 hours
10	Few Type C	Type B : 5.0 hours, Type C : 1.0 hours	23 hours
11	Few Type C	Type B : 4.5 hours, Type B : 2.5 hours	23 hours
12	Few Type C	Type B : 4.5 hours, Type C : 2.0 hours	23 hours
13	Few Type C	Type B : 4.5 hours, Type C : 1.5 hours	23 hours
14	Few Type C	Type B : 4.5 hours, Type C : 1.0 hours	23 hours
15	Few Type C	Type B : 4.0 hours, Type B : 3.0 hours	23 hours
16	Few Type C	Type B : 4.0 hours, Type B : 2.5 hours	23 hours
17	Few Type C	Type B : 3.5 hours, Type B : 3.0 hours	23 hours

[Phase 1] Aggregate Schedule For Elective Patients

- Elective surgery request arrives
- Scheduler looks at the partial schedule of that day
- If including it conforms to one of patterns, then allocate the surgery

Daily Pattern	OR_1	OR_2 or OR_3	Approximately Total hours
1	Few Type C	Type A: 8.0 hour	22 hours
2	Few Type C	Type A : 7.5 hour	22 hours
3	Few Type C	Type A : 7.0 hour	22 hours
4	Few Type C	Type A : 6.5 hour	22 hours
5	Few Type C	Type A : 6.0 hour, Type C : 1.0 hour	22 hours
6	Few Type C	Type B : 5.5 hour, Type C : 1.5 hour	22 hours
7	Few Type C	Type B : 5.5 hour, Type C : 1.0 hour	22 hours
8	Few Type C	Type B : 5.0 hour, Type C : 2.0 hour	22 hours
9	Few Type C	Type B : 5.0 hour, Type C : 1.5 hour	22 hours
10	Few Type C	Type B : 5.0 hour, Type C : 1.0 hour	22 hours
11	Few Type C	Type B : 4.5 hour, Type B : 2.5 hour	22 hours
12	Few Type C	Type B : 4.5 hour, Type C : 2.0 hour	22 hours
13	Few Type C	Type B : 4.5 hour, Type C : 1.5 hour	22 hours

[Phase 1] Aggregate Schedule For Elective Patients

- Elective surgery request arrives
- Scheduler looks at the partial schedule of that day
- If including it conforms to one of patterns, then allocate the surgery
- Otherwise, the scheduler will work with patients and assign the surgery to another day that is convenient to the patient.
- Phase 1 ensures that appropriate workload is assigned to the 3 ORs and that a proper mix of short, medium and long surgery durations is selected.

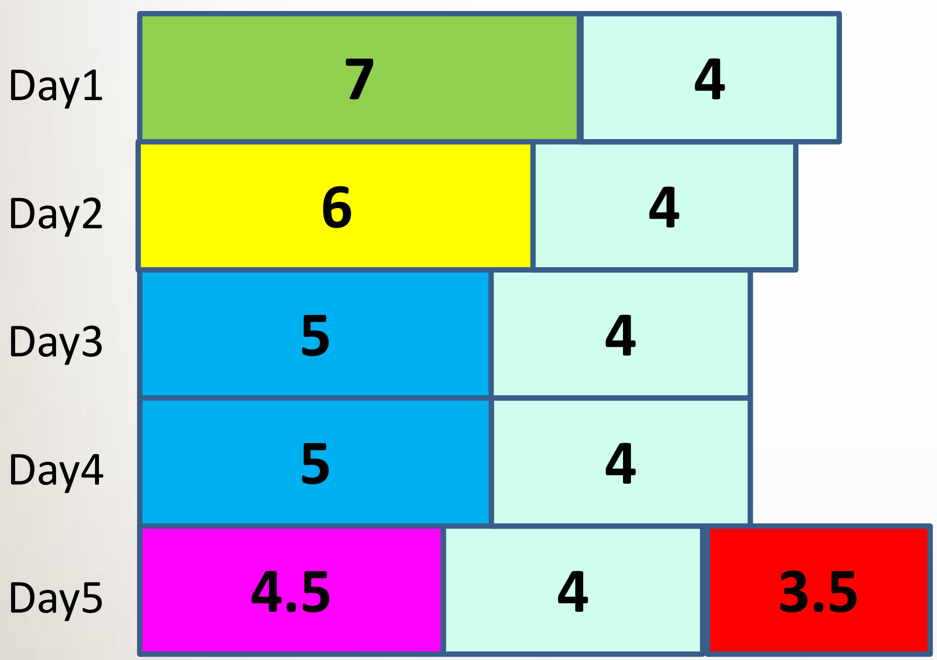
Phase 1: Aggregate Schedule

[Phase 1] Given weekly aggregate schedule

- Longest Processing Time First Rule (LPT).
  - Sort the surgeries in descending order
  - Assign the longest processing surgery that is not assigned to the day which has the minimum flow time first.

[Phase 1] Given weekly aggregate schedule

- Longest Processing Time First Rule (LPT).
  - Example: 31 elective surgeries in week 3



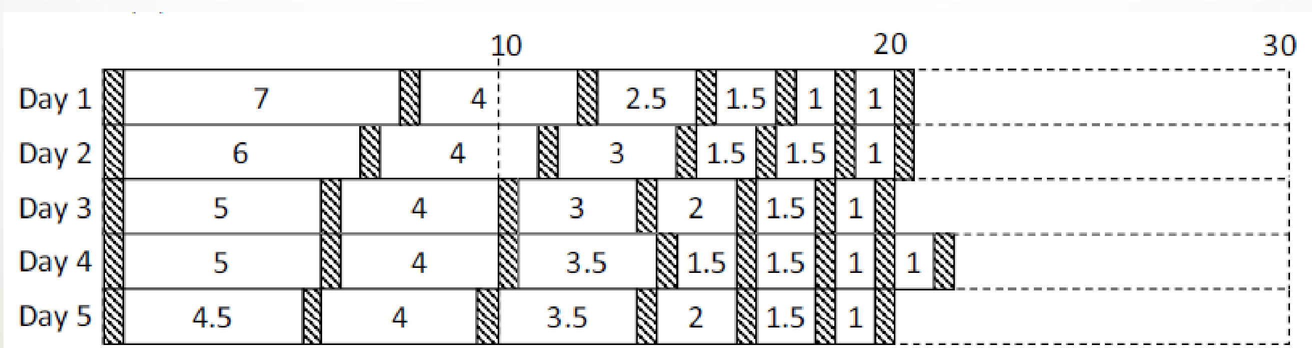
Preparation (Cleaning)

Surgery Time (hour)	Week $j=3$
1	7
1.5	7
2	2
2.5	1
3	2
3.5	2
4	5
4.5	1
5	2
5.5	0
6	1
6.5	0
7	1
7.5	0
Total Number of Surgeries	31
Total Surgery hours	84.5
Total preparation hours	15.5

[Phase 1] Given weekly aggregate schedule

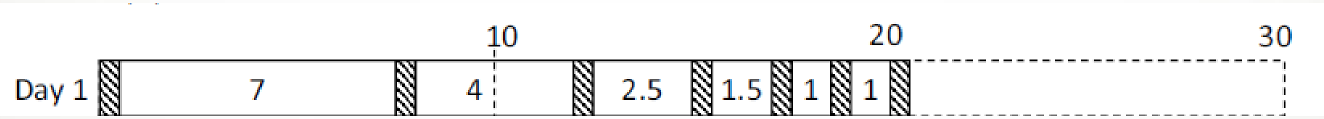
- Longest Processing Time First Rule (LPT).
  - Sort the surgeries in descending order
  - Assign the longest processing surgery that is not assigned to the day which has the minimum flow time first.

- There are 31 elective surgeries with three rooms in week 3



[Phase 2] Daily Schedule

- "n" electives cases in "m" ORs
- MIP model – Proved that it is Strongly NP-Hard, even when m=2
- [Need] The Overlap time of surgeries: **no more than 2 hours**
- Heuristic
- **Consider the six surgeries to be scheduled.**



[Phase 2] Daily Schedule with Heuristics

- LPT(m-k)-SPT(k) Rule, where k=1.

Heuristic $\mathbf{H_D}$ (The LPT(m-1)-SPT(1) Rule)

Begin

S is an ordered set of n surgeries **arranged according to LPT** ', i.e., $p_1 \geq p_2 \geq \ldots \geq p_n$.

Schedule last job in S on OR_1 and remove last job from S.

While ($S \neq \emptyset$) do

Step 1: Find **the earliest available OR** in $\{OR_1, OR_2, \ldots, OR_m\}$.

Step 2: If earliest available OR is OR_1, schedule last job in S on OR_1 and remove last job from S. Otherwise, schedule first job in S on earliest available OR among $\{OR_2, OR_3, \ldots, OR_m\}$ and remove first job from S.

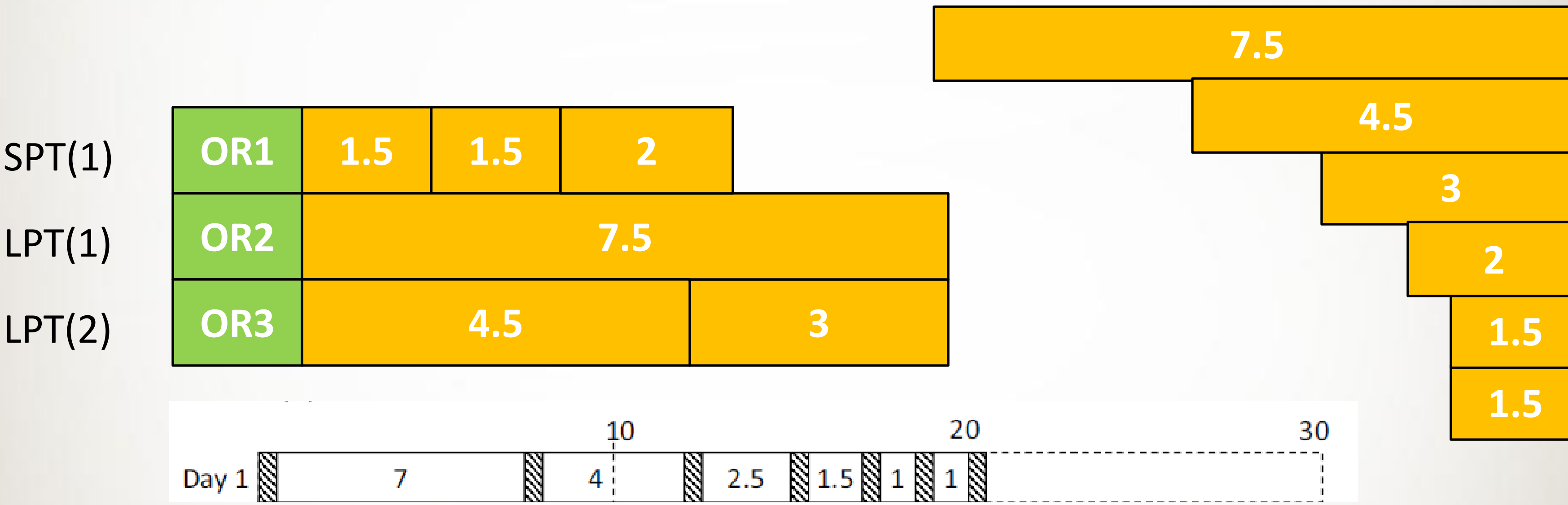
End(while)

Output: A feasible schedule for surgeries in S.

End

[Phase 2] Daily Schedule with Heuristics

- LPT(m-k)-SPT(k) Rule, where k=1.
- SPT machine: OR1



Daily Pattern	OR_1	OR_2 or OR_3	Approximately Total hours
1	Few Type C	Type A: 8.0 hour	22 hours
2	Few Type C	Type A : 7.5 hour	22 hours
3	Few Type C	Type A : 7.0 hour	22 hours
4	Few Type C	Type A : 6.5 hour	22 hours

[Phase 2] Intuition behind the LPT(m-k)-SPT(k) rule

The motivation behind the LPT($m-1$)–SPT(1) heuristic is based on the following. There are two objectives: the first one is a balancing of the loads assigned to the m ORs (in order to minimize overtime). The second one is the minimization of the maximum time in between two successive BIMs. Applying LPT to $m-1$ ORs has as goal the minimization of the first objective. However, if LPT would have been applied to all m ORs, then in the beginning of the process all ORs would have to deal with long surgery durations and the times in between successive BIMs (e.g., the time till the first BIM) may at times be too long. In order to remedy this, we apply SPT to one of the ORs. If an emergency then arrives at some time in the beginning of the process, the amount of time till the next BIM should be relatively short (and it would most likely occur in the OR that had been assigned the surgeries with short durations).

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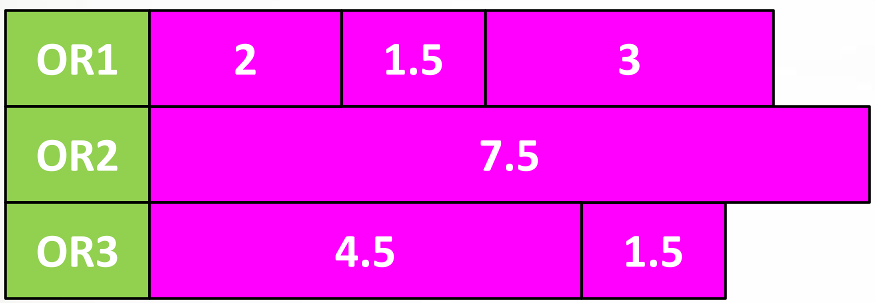
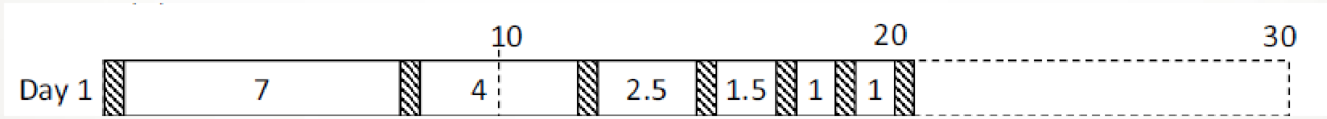
[Phase 2] Daily Schedule with MIP Model

- Mixed Integer Program for minimizing the overall cost.
- [Need] The Overlap time of surgeries: <u>**no more than 2 hours**</u>





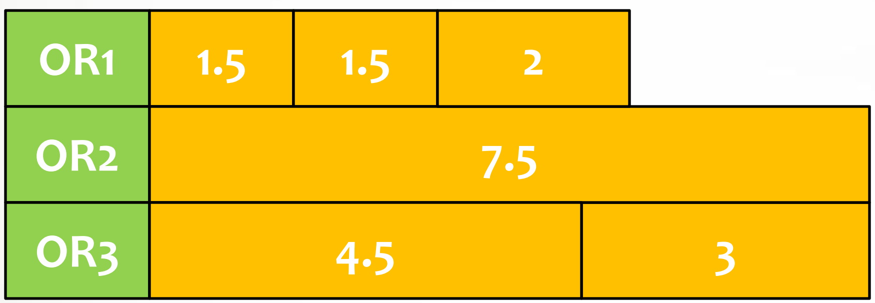
[Phase 3] Arrival Pattern for Emergency Patients

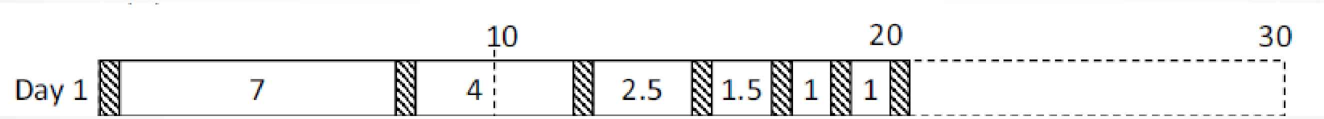
- The emergency patients who arrive during operating hours (i.e., 7 am to 5 pm), since they have priority over elective patients.

- The emergency surgery arrivals fits a Poisson distribution under 5% significant level.
  - On average 6.17 emergency patients per month randomly arrive.

[Phase 3] Rescheduling process

- The (Revised) Online LPT(m-k)-SPT(k) Rule
- The Online MIP Model





[Phase 3] Rescheduling process: Online LPT(m-k)-SPT(k) Rule

Heuristic $\mathbf{H_O}$ (The Online LPT(m-1)-SPT(1) Rule)

Begin

Input: **S** is an ordered set of n elective surgeries (including surgery times) and

E is an ordered set of emergency patients (including surgery times and arrival times) sorted by arrival times.

Run heuristic $\mathbf{H_D}$ on **S**.

Output: A feasible schedule for surgeries in **S**.

While ($\mathbf{E} \neq \emptyset$) do

Suppose first emergency in **E** arrives at time t_1 with surgery time p_e.

Input: A subset of surgeries ($\mathbf{S_b}$), which includes (i) those ongoing at time t_1 and (ii) those already completed before time t_1, are fixed.

Step 1: Find the earliest available OR (its completion is denoted by t_2).

Schedule first emergency surgery in **E** and remove this surgery from **E**.

Step 2: Set $\mathbf{S} = \mathbf{S} - \mathbf{S_b}$ and apply heuristic $\mathbf{H_D}$ to the remaining surgeries in **S**.

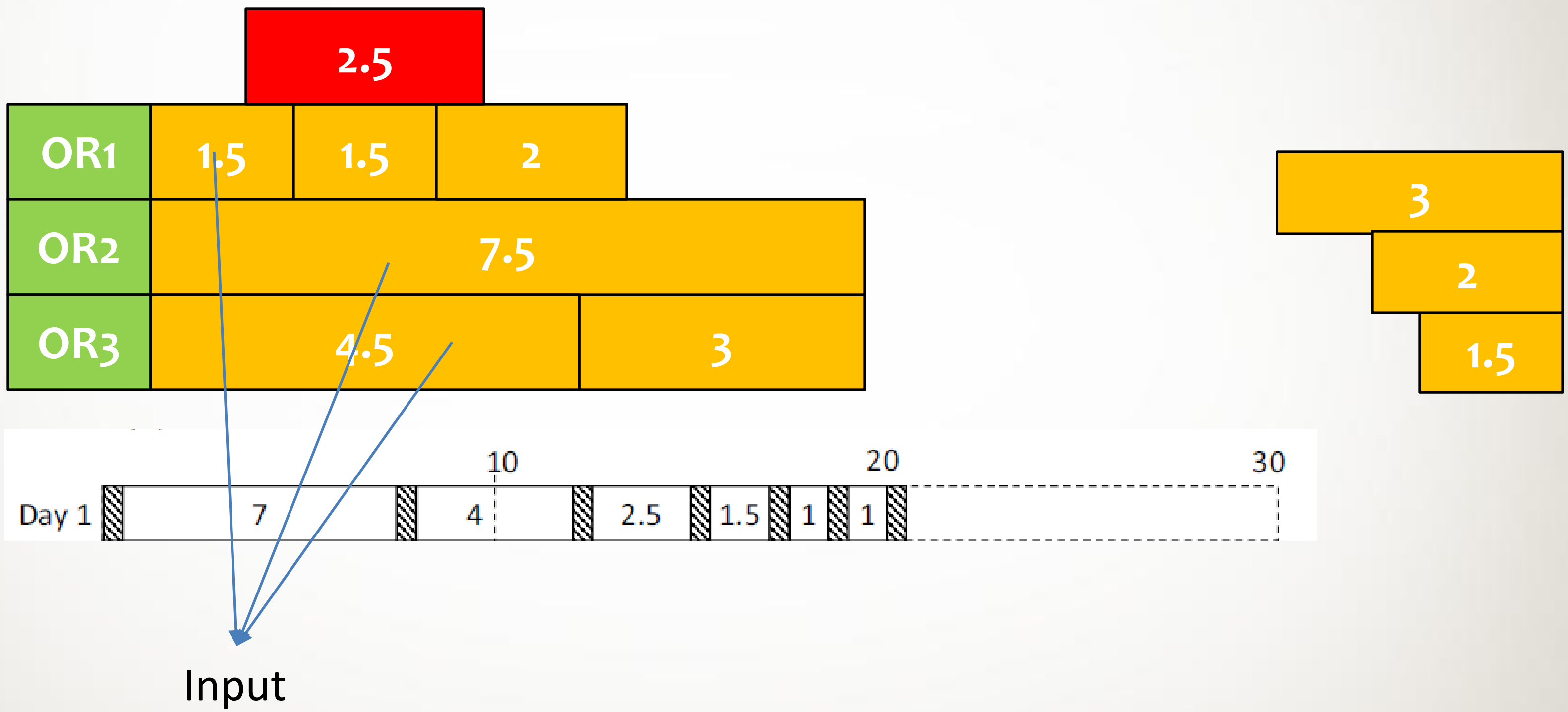
End(while)

Output: A feasible schedule for surgeries in **S** as well as **E**.

End

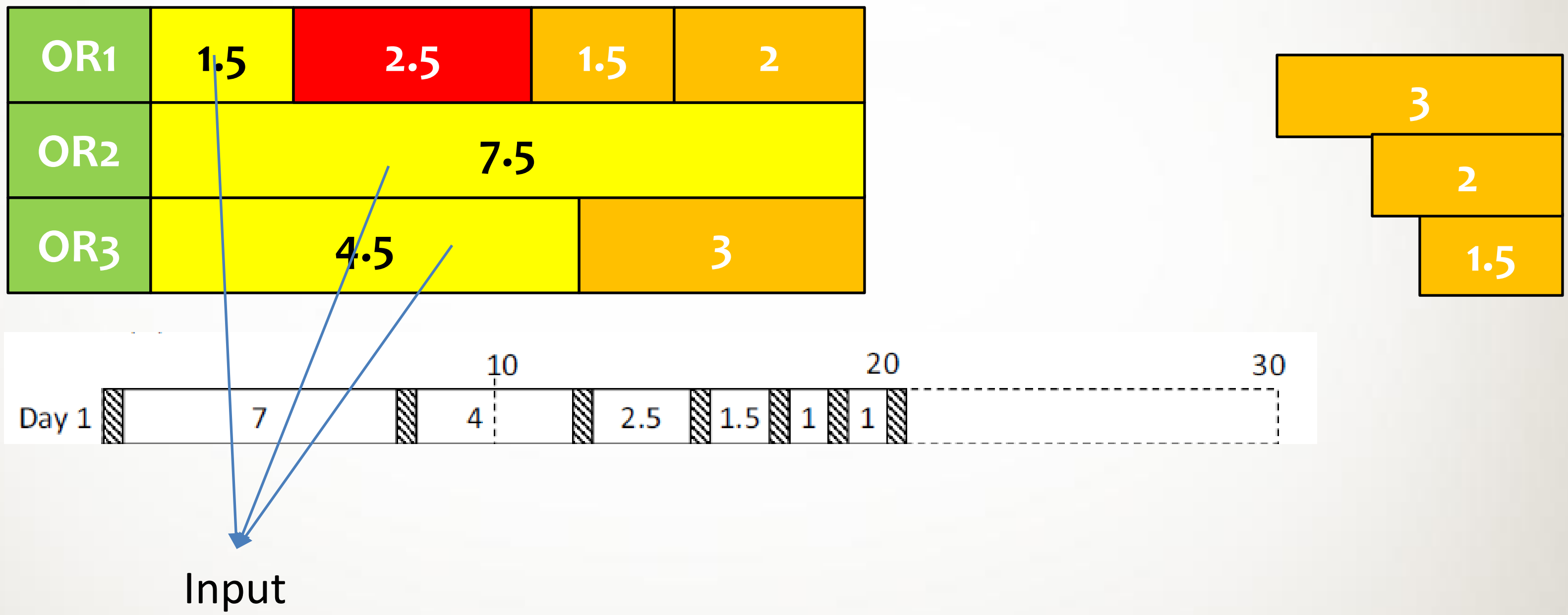
[Phase 3] Rescheduling process

- The Online LPT(m-k)-SPT(k) Rule
- SPT machine: OR1



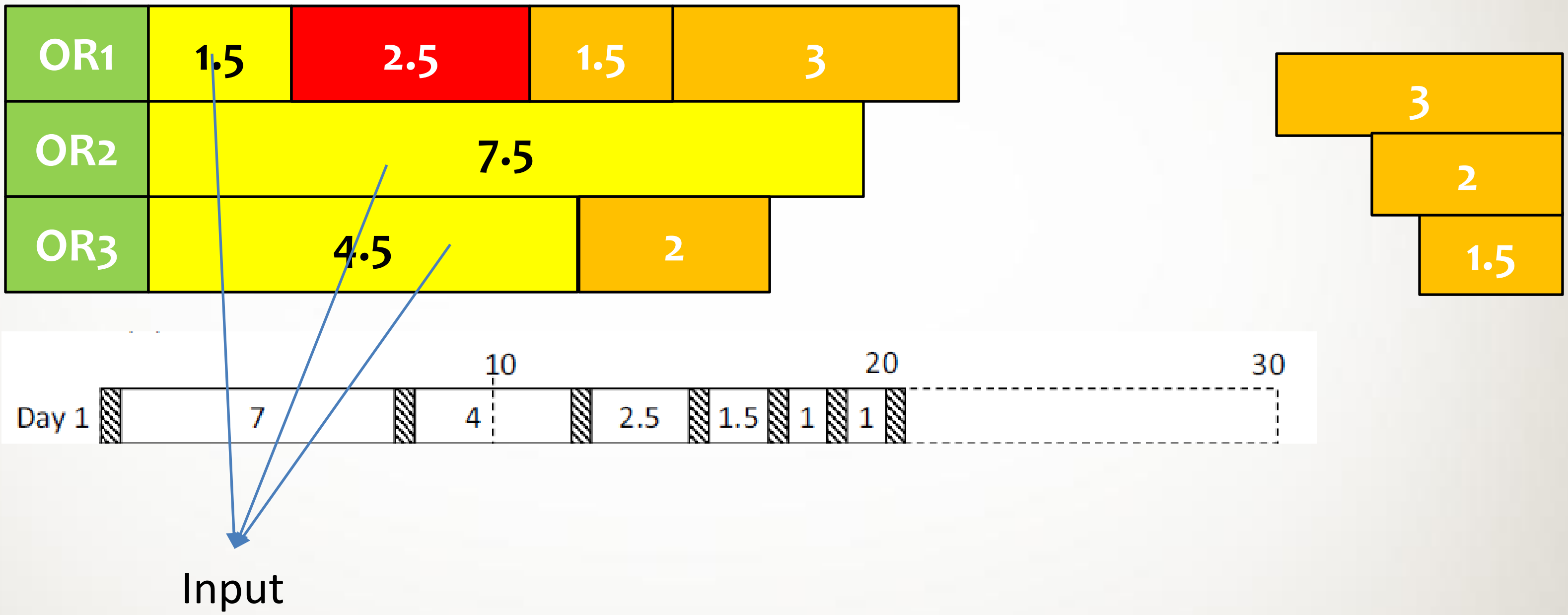
[Phase 3] Rescheduling process

- The Online LPT(m-k)-SPT(k) Rule
- SPT machine: OR1



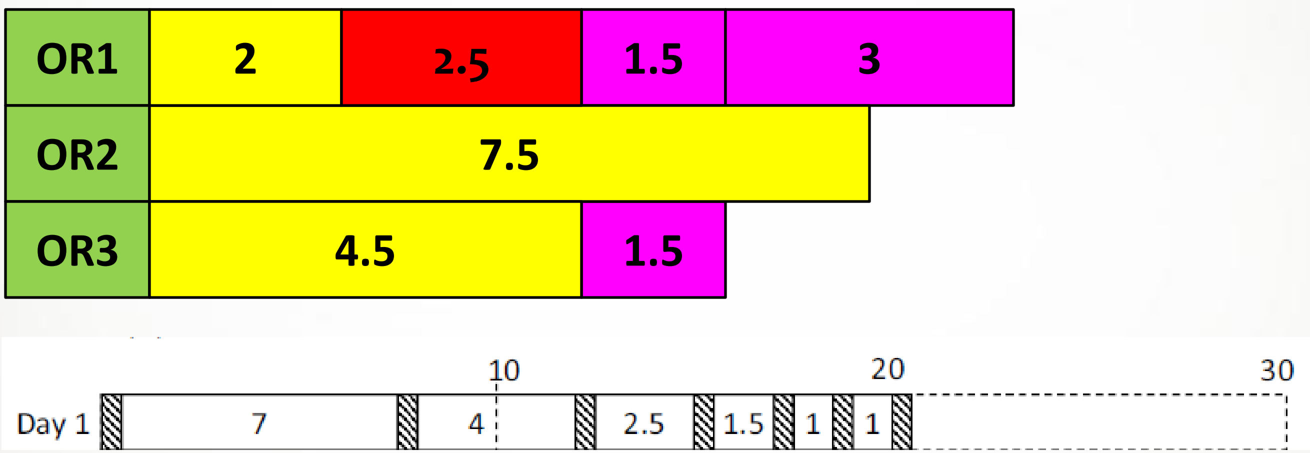
[Phase 3] Rescheduling process

- The Revised Online LPT(m-k)-SPT(k) Rule
- SPT machine: OR1 → **OR3**



[Phase 3] Rescheduling process

- The Online MIP Model



Contribution of this research

Jung, Pinedo, Sriskandarajah, and Tiwari: *Scheduling Elective Surgeries at Shared ORs*
Production and Operations Management 28(6), pp. 1407–1430, © 2019 Production and Operations Management Society 1409

Table 1 Classification of Papers Related to Our Study in Terms of Type and Level of Decisions

		SCSP, Multi-ORs		Emergency patients		
SCAP	SCSP, Single OR	Deterministic	Stochastic	Shared OR	DEOR	Rescheduling
Marcon et al. (2003), Hans et al. (2008), and Fei et al. (2009)	Weiss (1990), Wang (1993), Denton and Gupta (2003), Denton et al. (2007), Gupta (2007), and Guda et al. (2016)	Blake and Donald (2002), Velasquez and Melo (2005), Jebali et al. (2006), Pham and Klinkert (2008), Cardoen et al. (2010b), Riise and Burke (2011), Marques et al. (2012); Vijayakumar et al. (2013), and Zhao and Li (2014)	Denton et al. (2010) and Batun et al. (2011)	Gerchak et al. (1996), Lamiri et al. (2008a), Pham and Klinkert (2008), and Zonderland et al. (2010)	Bhattacharyya et al. (2006), Wullink et al. (2007), Li and Stein (2008), and Ferrand et al. (2014)	Gul et al. (2011), Van Essen et al. (2012), Erdem et al. (2012), Gul et al. (2015)
Our paper		Our paper	Our paper	Our paper	Our paper	Our paper

SCAP: surgical case assignment problem; SCSP: surgical case sequencing problem

Conclusion

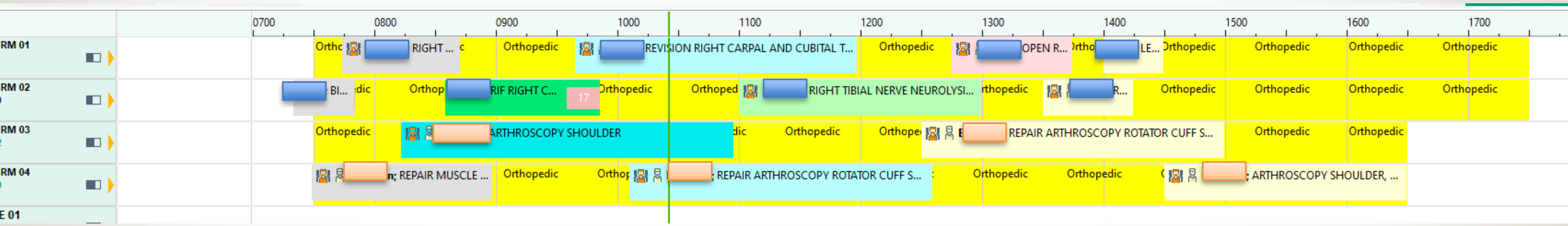
- The integrating schedule from Phase 1 to 3.

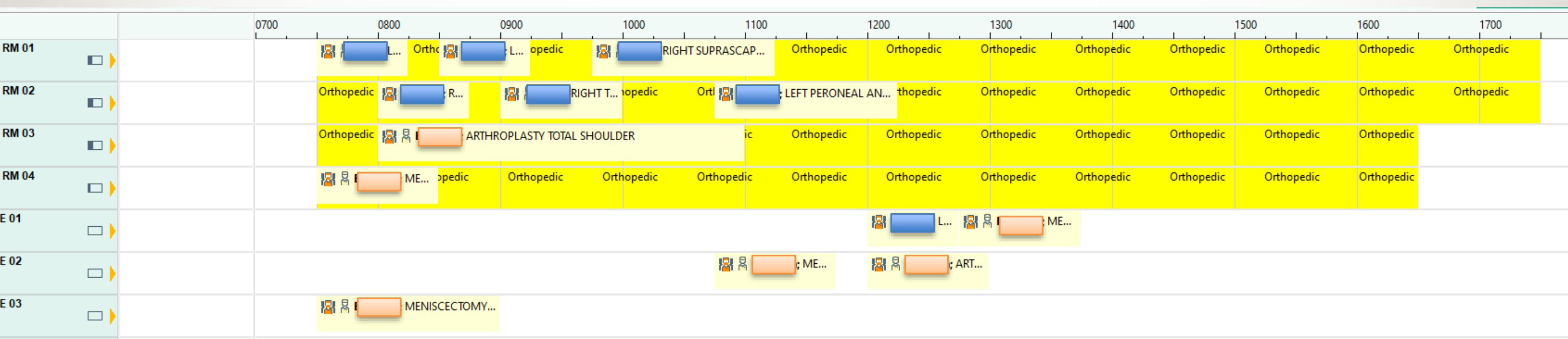
Phase 1	Phase 2	Phase 3
Daily/Weekly Aggregate Schedule	**Daily Schedule (Elective Patients)**	**Rescheduling (Elective & Emergency)**
• Number of Patients (Best Combination)	• Heuristics • Model MIP	• Heuristic Online • Model MIP Online

Rescheduling process with Stochastic Surgery Duration

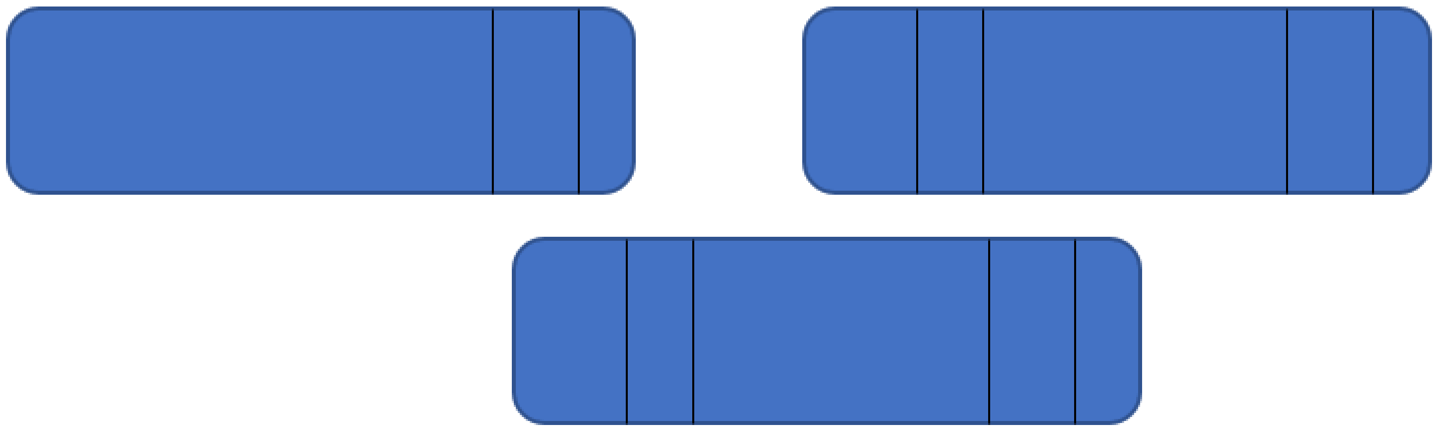
Potential Future Research Themes

Flip-Room Schedules





Flip-Room Scheduling Components



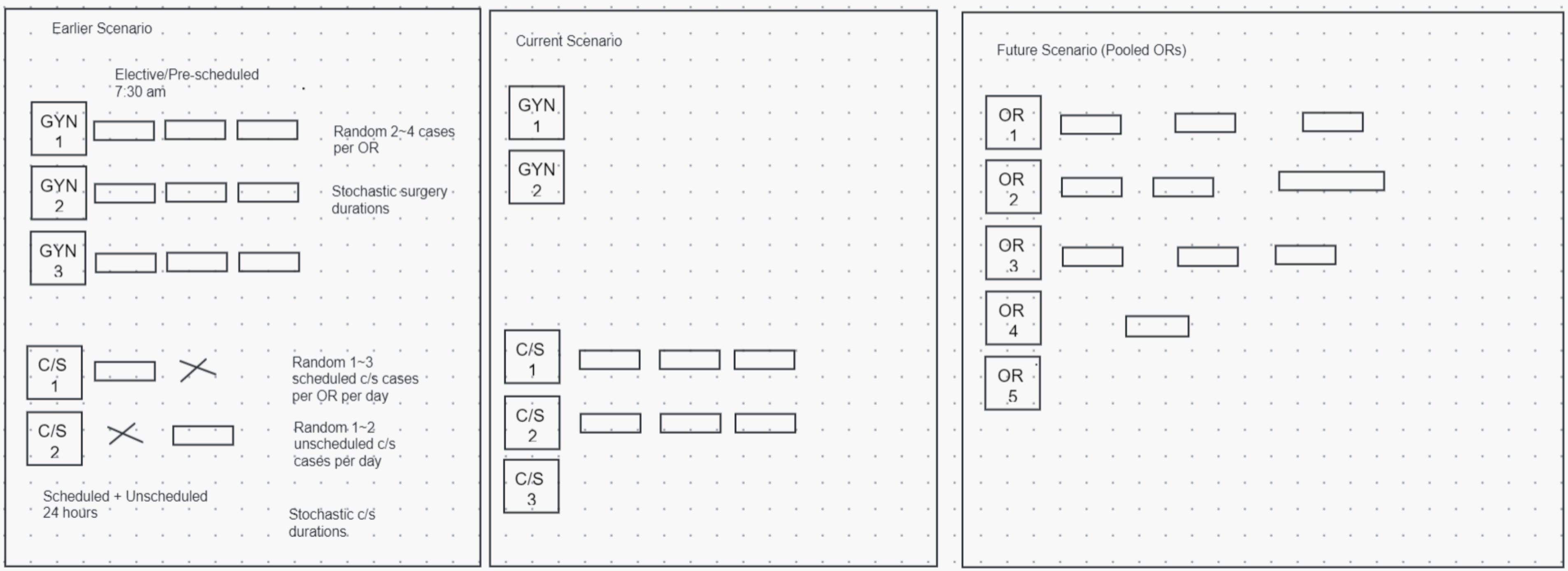
	Subsequent Case			
		Wheels In (2)	Anesthesia Ready (3)	Incision (4)
Prior Case	Last Procedure Closing (1)			
	Incision Closed (5)			
	Wheels Out (6)			

Flip-Room Surgeons Scheduling Pattern

MEDIAN TIME (MINUTES)										
Prior Case →	**Last Procedure Closing**			**Incsion End**			**Out of OR**			**Case**
Subsequent Case →	**In OR**	**Anes. Ready**	**Incision Beg.**	**In OR**	**Anes. Ready**	**Incision Beg.**	**In OR**	**Anes. Ready**	**Incision Beg.**	**Volume**
	6	15	11	-27	-16	3	-33	-22	-2	10
	8	21	32	-15	-10	8	-21	-14	4	10
	0	5	21	-13	-7	8	-16	-9	5	47
	7	17	29	-6	2	17	-13	-7	12	10
	12	24	46	-19	-7	16	-22	-10	11	23
	10	18	27	-1	9	16	-3	4	13	16
	-18	-4	17	-32	-26	-10	-34	-29	-13	44
	-14	-1	15	-27	-23	-10	-25	-27	-15	59
	16	22	25	-3	8	34	-7	1	26	18
	3	11	22	0	8	17	-6	3	14	18
	-1	9	19	-2	8	18	-9	0	11	14
	-10	-2	25	-23	-15	13	-27	-20	7	52
	9	21	35	-18	-9	9	-20	-12	7	9
	0	10	28	-15	-9	10	-18	-12	5	37
	2	9	24	-7	-4	12	-7	-2	11	11

A negative number implies that the subsequent case's event occurred before the prior case's event.

Extending the Shared-ORs Research



Extreme case when an OR must always be available for an emergency case

Perioperative bed capacity planning guided by theory of constraints

Publisher: IEEE   Cite This   PDF

Vikram Tiwari ; Warren S. Sandberg   All Authors

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https://pubsonline.informs.org/journal/msom

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Adaptive Capacity Planning for Ambulatory Surgery Centers

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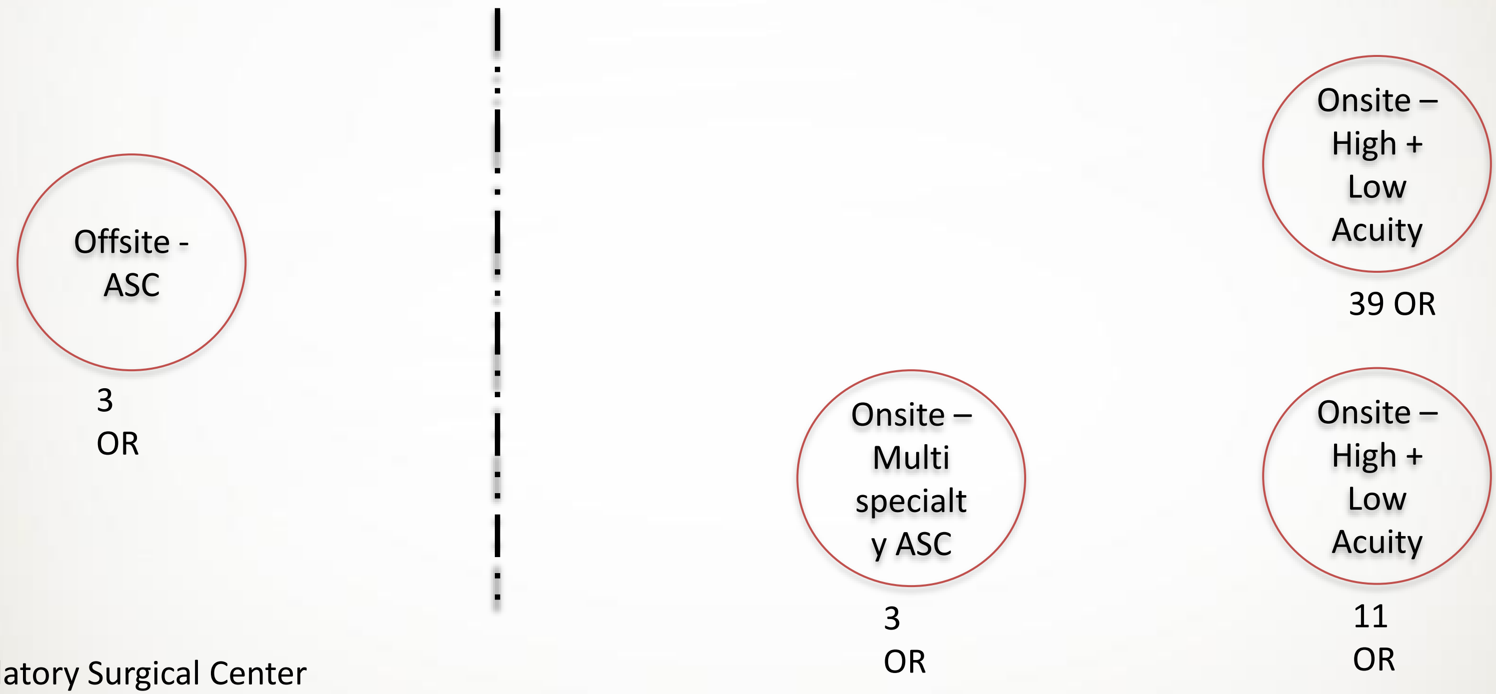
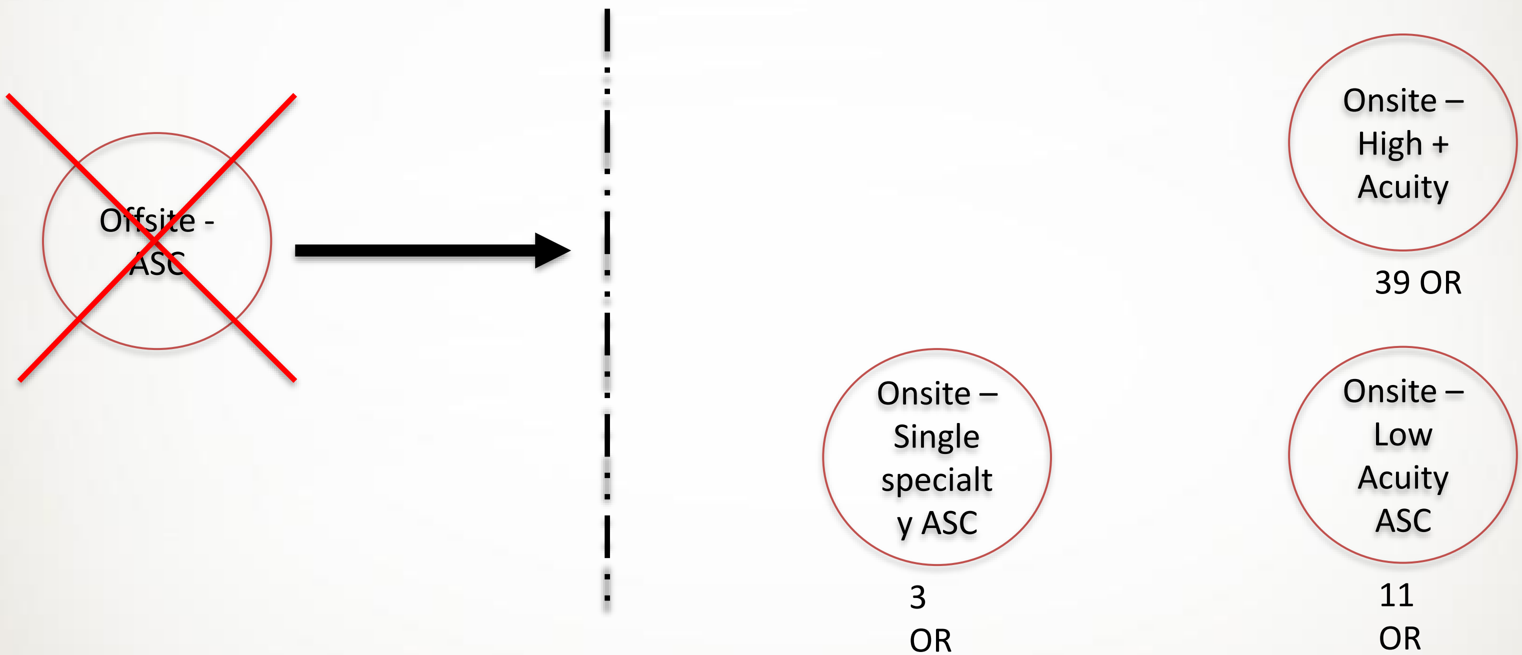
* Corresponding author

Current State

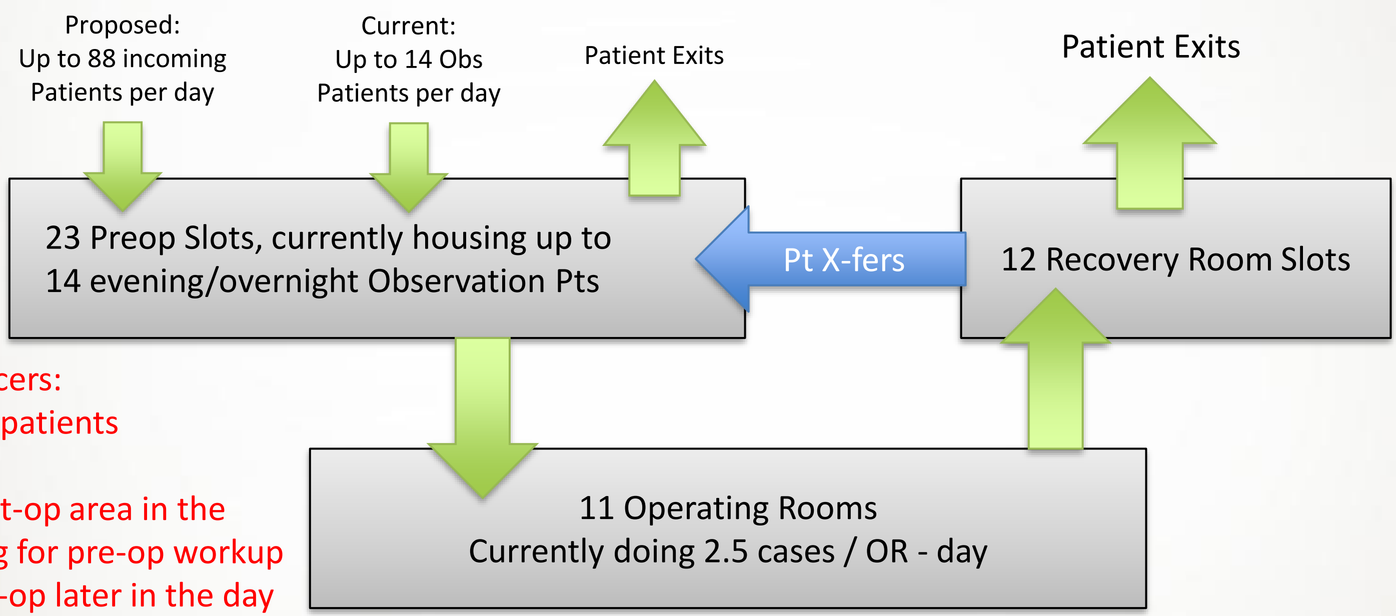


ASC: Ambulatory Surgical Center

Future State



Current and proposed patient flow in the perioperative arena comprised on 11 ORs



Decision Influencers:

1. Observation patients
2. Flexibility:
   a) Use post-op area in the morning for pre-op workup
   b) Use pre-op later in the day to recover late stage post-op patients

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The issue – capacity management

Financial considerations drove merging of offsite services to onsite locations → Services' reconfiguration among onsite locations planned → Plan entails converting an 11 OR site to a low-acuity surgical center

GIVEN THESE CONSTRAINTS

ANSWER THE FOLLOWING CAPACITY ISSUES

Do we have enough pre & post-op beds to satisfy higher vol. & shorter case lengths? → How many 23-hr Obs patients can we continue to hold in pre-op? → Is the expected increase in OR case volume going to overwhelm our capacity?

Simulation

- Deterministic approaches insufficient, need stochastic (probabilistic) methods
  - Computer simulation of patient flows
- However, how detailed should be the simulation logic to model capacity needs?
  - Incorporate service/surgeon block schedules?
  - Incorporate elective case booking pattern?
  - Incorporate staffing and shift schedules?
- Back to the basics …… “Operations Mgmt 101”

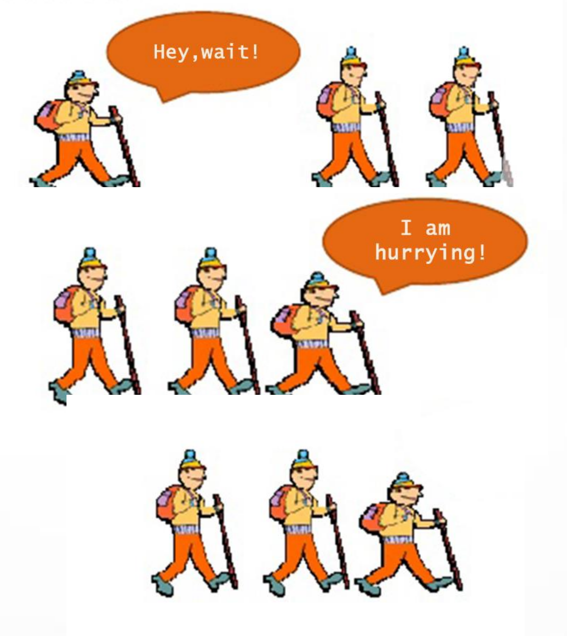
Constrained Scheduling / Bottleneck Scheduling / Weakest Link

Herbie: The slowest hiker

Herbie at the back of the line,
a half mile behind the lead hiker

Herbie at the front of the line,
huffing and puffing away with
everyone behind him

Herbie's load lightened and shared,
the whole troop makes good time



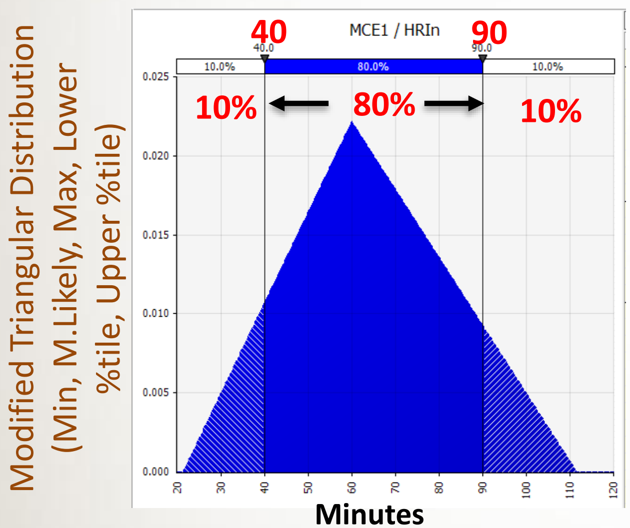
The Goal by Eliyahu Goldratt

Herbie = OR

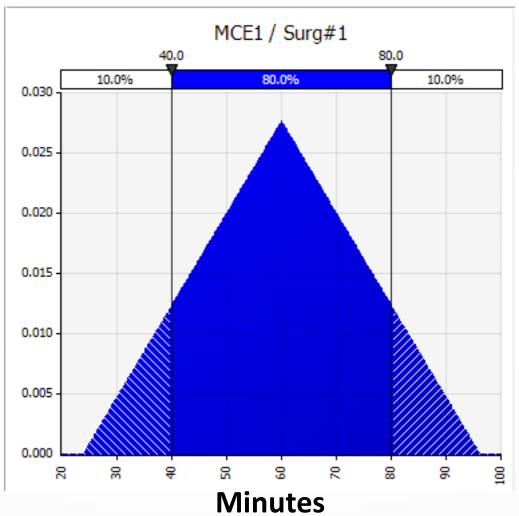
Make other stages of the periop match the rate of flow of the OR

Simulation Model*

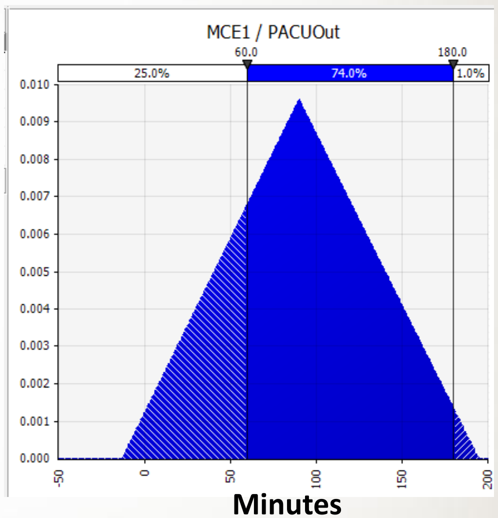
How many patients at what different times of the day will be in the pre/post op stage, if we fully load the system (that is, keep all the 11 ORs fully occupied throughout the entire day)?



Pre Op Times Distribution



In Room Times Distribution



Post Op Times Distribution

*@Risk for Excel, Palisade Corporation

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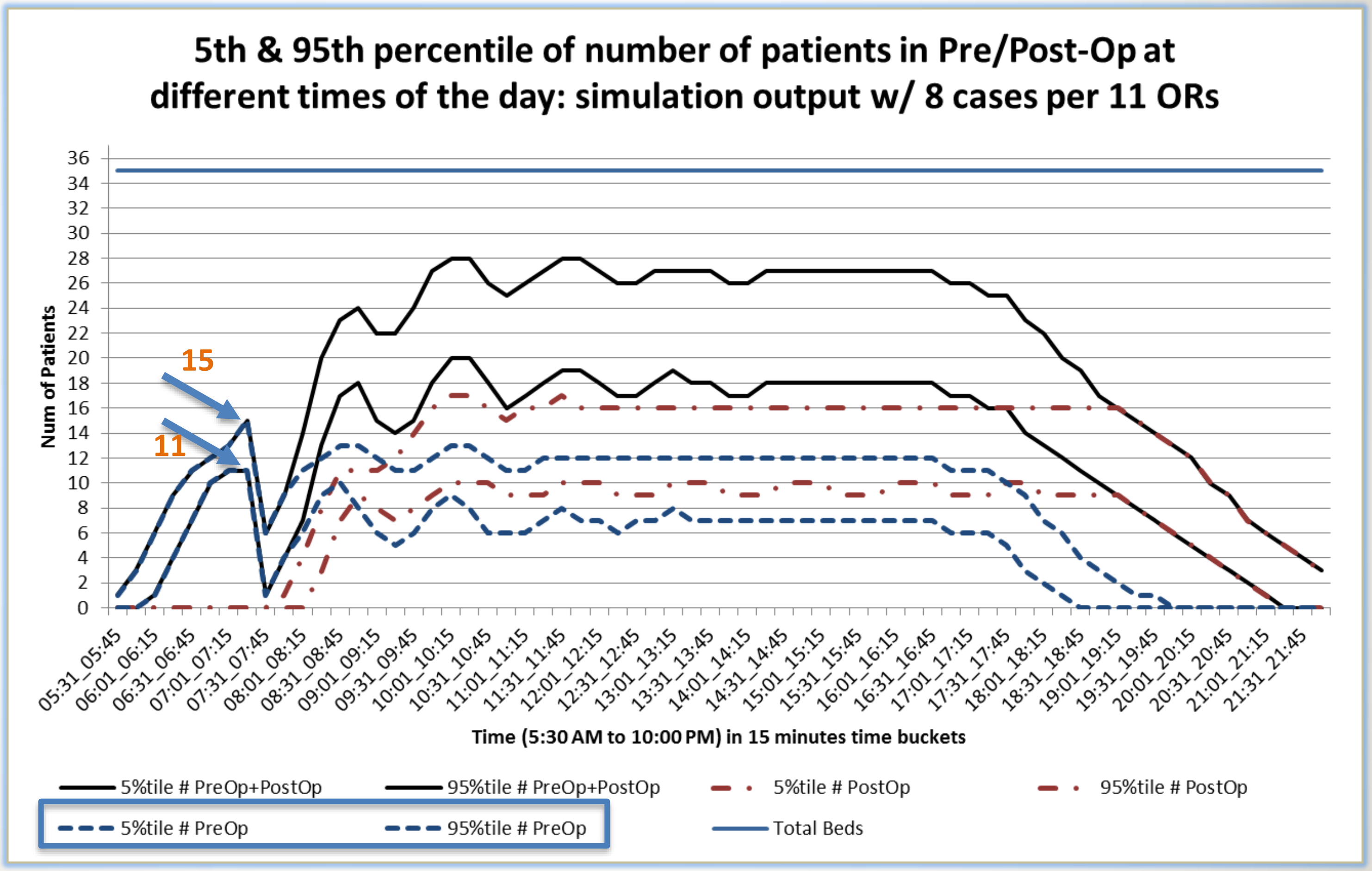
Simulation Output – focus on Preop

Current:
23 HR - 14 Obs =
9 HR beds
enough to start
11 ORs

Recommendation:
1) 11-15 HR beds needed to start 11 ORs = 23 HR – 12 to 8 Obs
2) 15 HRbeds sufficient, don't need 22!
3) Rest of the day bet. 6 to 12 HR beds are needed.



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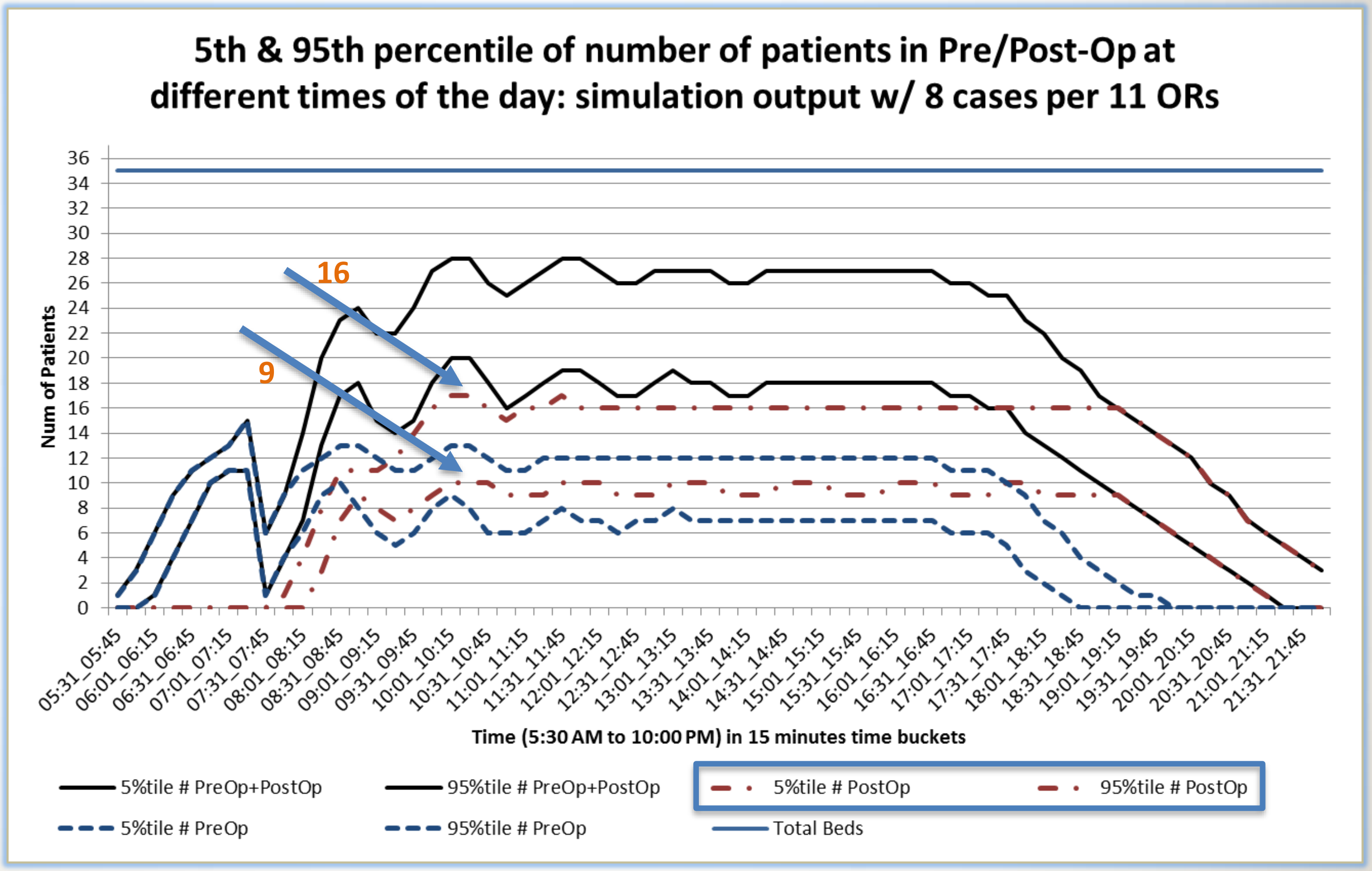
Simulation Output – focus on Postop

Current: 12 PACU

Recommendation:

1) 12 PACU sufficient, but move late stage recovery patients to HR
2) Timely discharge of overnight Obs patients; target before 11 am.



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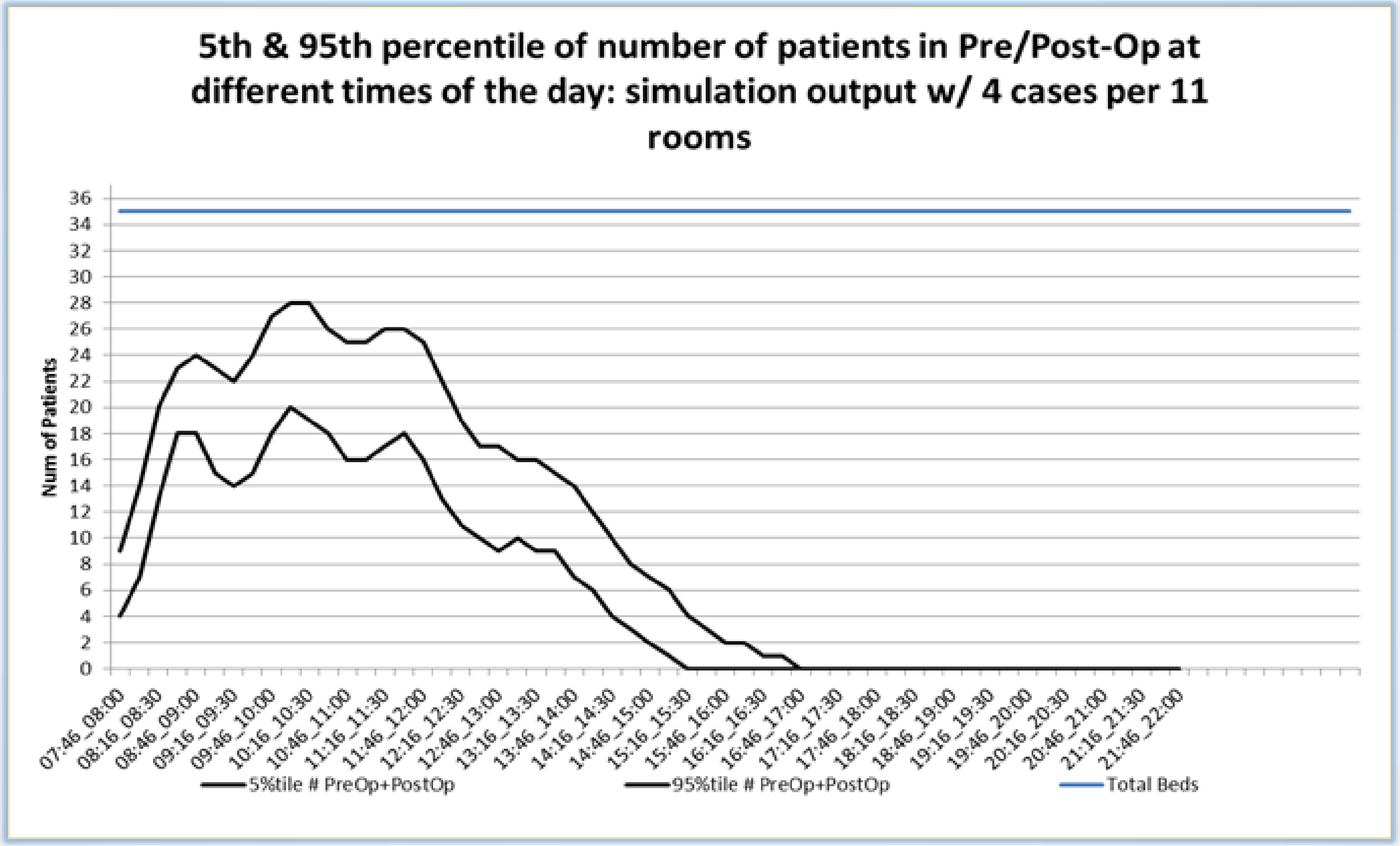

5th & 95th percentile of number of patients in Pre/Post-Op at different times of the day: simulation output w/ 4 cases per 11 rooms
Num of Patients
36
34
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
2
0
07:46_08:00
08:16_08:30
08:46_09:00
09:16_09:30
09:46_10:00
10:16_10:30
10:46_11:00
11:16_11:30
11:46_12:00
12:16_12:30
12:46_13:00
13:16_13:30
13:46_14:00
14:16_14:30
14:46_15:00
15:16_15:30
15:46_16:00
16:16_16:30
16:46_17:00
17:16_17:30
17:46_18:00
18:16_18:30
18:46_19:00
19:16_19:30
19:46_20:00
20:16_20:30
20:46_21:00
21:16_21:30
21:46_22:00
5%tile # PreOp+PostOp
95%tile # PreOp+PostOp
Total Beds

Outcomes & Decisions

- Deterministic analysis (based on averages):
  - 12 pre/post-op beds sufficient
  - Current policy of holding 14 overnight Obs patient in pre-op will be fine even in the future
- Stochastic analysis (from simulation models):
  - Pre & post-op bed capacity sufficient, if, a max. of 9 overnight Obs patients in pre-op, and late-stage post-op patients moved to pre-op beds later in the day, and Obs patients discharged in a timely manner earlier in the day vacating pre-op beds
- Non-intuitive interesting insight:
  - higher OR case volume ≠ more pre/post-op beds; it just means a longer day

Adaptive Capacity Planning For Ambulatory Surgery Centers

Seokjun Youn[1] (syoun@email.arizona.edu)

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[1]University of Arizona, [2]Texas A&M University, [3]Vanderbilt University Medical Center

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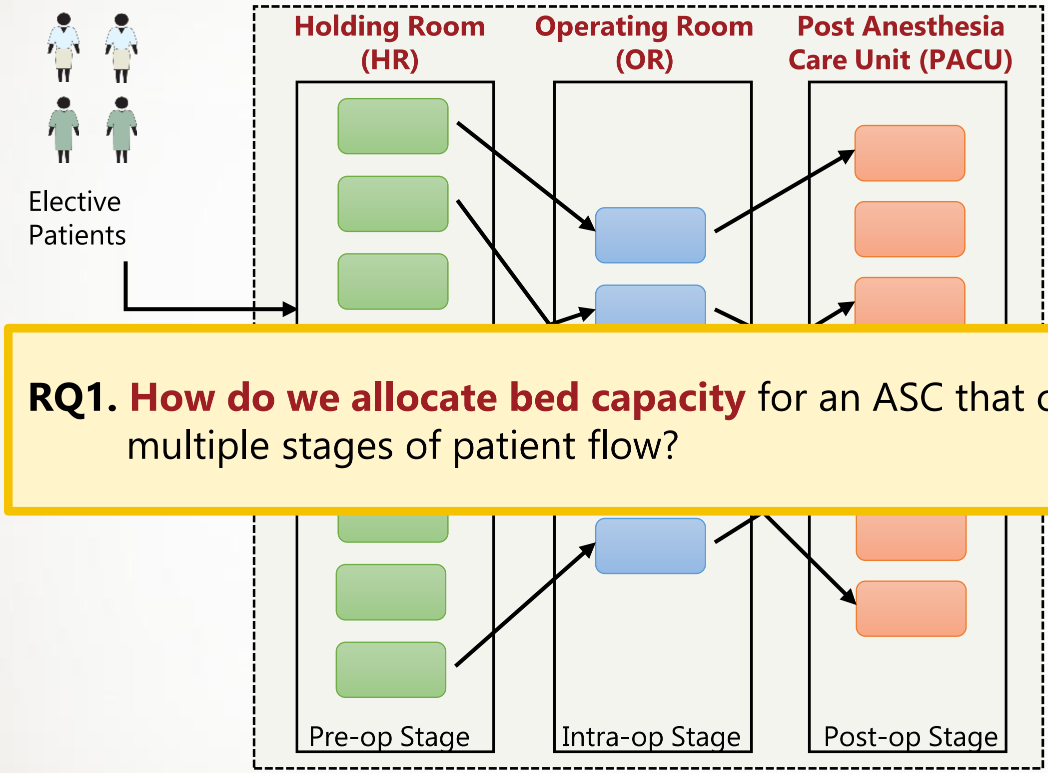
Background: Patient Flow at ASCs



RQ1. How do we allocate bed capacity for an ASC that comprises multiple stages of patient flow?

- ❑ Sequential stages with multiple beds in each stage: Hybrid Flow Shop (HFS) (Pinedo 2015)

Literature & Research Objective

Hybrid Flow Shop

- Gicquel et al. (2012)
- Liu and Karimi (2008)
- Thornton and Hunsucker (2004)
- …

Focus on scheduling **with FIXED capacity** in manufacturing context.

Simulation in ASC Settings

- Tiwari and Sandberg (2016)
- Price et al. (2011)
- White et al. (2011)
- Marcon et al. (2003)

Provide **relative performance** without optimality information.

This study provides an Adaptive Capacity Planning tool,

- Informed by patient flow data using optimization models combined with data analytics ("*bottom-to-top*"),
- rather than regarding as a strategic decision ("*top-to-bottom*").

Sequence of ASC Capacity Planning

ASC Patient Flow Data Analysis

- Classify patient groups
- Obtain daily patient demand over weekdays

Adaptive ASC Capacity Planning

UB on #OR & #PACU	▪ ***Algorithm FFP1***
Optimal #OR & #PACU	▪ HFS formulation: ***Problem MILP1*** ▪ LBs of *MILP1* ▪ Optimal ORs and PACUs: ***Algorithm AdaptiveASC*** ▪ Heuristic for *MILP1*: ***Heuristic BasckwardASC***
Optimal #HR	▪ ***Minimum Cost Flow***

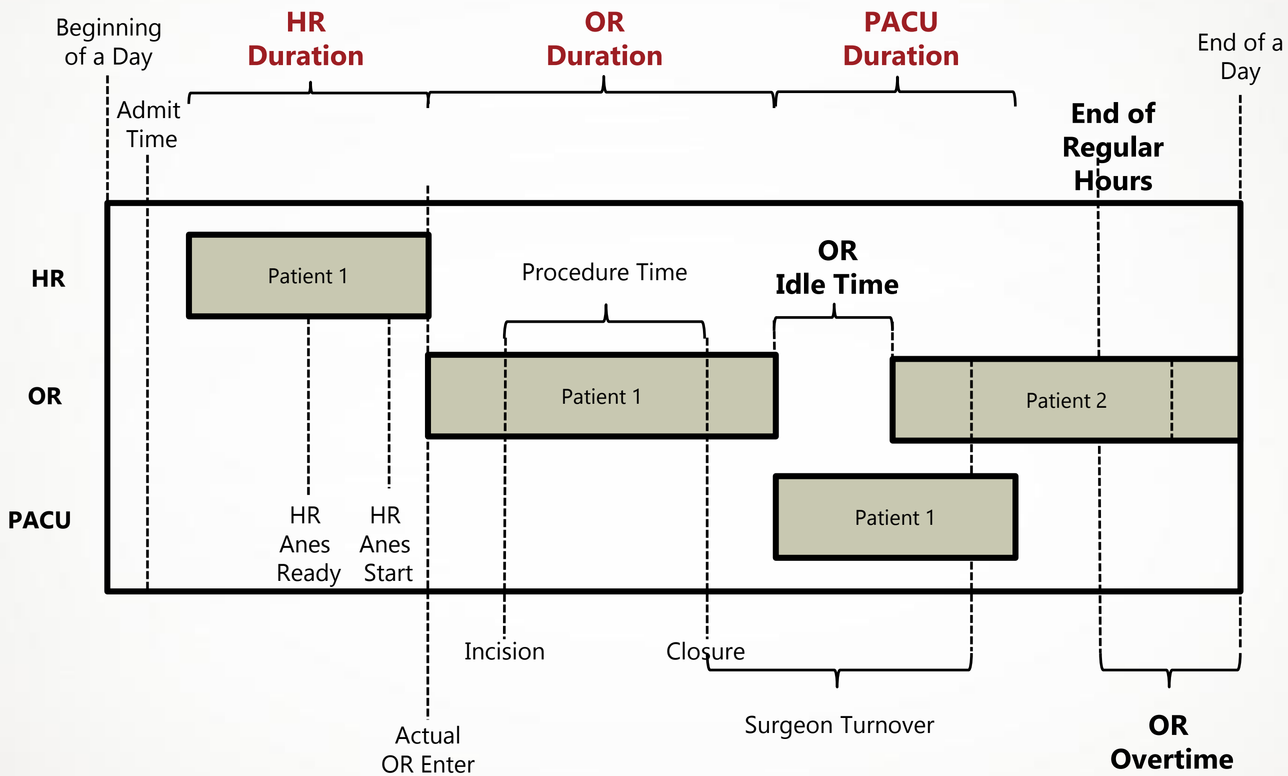
Computational Study and Implications

Model of Study: Settings

- **Objective**
  - Minimize a ASC's total cost of utilizing capacity over a planning horizon.
  - Trade-off: **overtime cost** and **capacity construction cost** of ASC resources.

- **Assumptions**
  - Beds at a given stage are identical.
  - ASC patients are elective.
  - ASC manager assigns patients.
  - Unit costs for the ASC resources:
    - Amortized OR Construction > Amortized PACU Construction > OR Overtime > PACU Overtime
  - Patient demand is exogenously determined by ASCs
    - In deterministic models
    - later relaxed in computational study

Model of Study: Constraints



No-wait constraint between stages

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HFS Formulation: Problem *MILP1*

Problem $MILP1$:

$$\min_{x_{isr}^t, y_{isr}^t, z_s^t, f_{is}} \underbrace{\sum_{s\in\mathcal{S}} \sum_{\boxed{r\in\mathcal{R}_s}} C_s^o h_{sr}}_{\text{Overtime Cost}} + \underbrace{\sum_{s\in\mathcal{S}} C_s^e R_s}_{\text{Amortized Capacity Construction Cost}}$$

subject to

$$\begin{aligned}
\sum_{\boxed{r\in\mathcal{R}_s}} \sum_{t=0}^{K-1} x_{isr}^t &= 1,\ \forall i\in\mathcal{I},\ \forall s\in\mathcal{S},\\
\sum_{i\in\mathcal{I}} \sum_{t'=\max\{0,t-p_{is}\}}^{t-1} x_{isr}^{t'} &\le 1,\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{1,\cdots,K\},\\
\sum_{t'=t}^{\min\{K-1,t+p_{is}-1\}} y_{isr}^{t'} &\ge p_{is}x_{isr}^t,\ \forall i\in\mathcal{I},\ ,\forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{0,\cdots,K-1\}\\
\sum_{i\in\mathcal{I}} \sum_{\boxed{r\in\mathcal{R}_s}} y_{isr}^t &= z_s^t,\ \forall s\in\mathcal{S},\ \forall t\in\{0,\cdots,K-1\},\\
\sum_{t=0}^{K-1} z_s^t &= \sum_{i\in\mathcal{I}} p_{is},\ \forall s\in\mathcal{S},\\
\sum_{\boxed{r\in\mathcal{R}_s}} \sum_{t=0}^{K-1} (t+p_{is})x_{isr}^t &\le f_{is},\ \forall i\in\mathcal{I},\ \forall s\in\mathcal{S},\\
\sum_{\boxed{r\in\mathcal{R}_1}} \sum_{t=0}^{K-1} t x_{i2b}^t &\ge f_{i1},\ \forall i\in\mathcal{I},\\
f_{i2}-(f_{i1}+p_{i2}) &\le 0,\ \forall i\in\mathcal{I},\\
(t+1-g_{sr}) &\le K\omega_{sr}^t,\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{0,\cdots,K-1\},\\
\sum_{i\in\mathcal{I}} y_{isr}^t &\le K(1-\omega_{sr}^t),\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{0,\cdots,K-1\},\\
g_{sr}-T &\le h_{sr},\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\\
x_{isr}^t,\ y_{isr}^t,\ w_{sr}^t &\in \{0,1\},\ \forall i\in\mathcal{I},\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{0,\cdots,K-1\},\\
z_s^t,\ f_{is}\ g_{sr}\ h_{sr} &\ge 0,\ \forall s\in\mathcal{S},\ \forall r\in\mathcal{R}_s,\ \forall t\in\{0,\cdots,K-1\}
\end{aligned}$$

Notice that the capacity $\mathcal{R}_s$ cannot be decision variables.

i: Patient
s: Stage
r: Room
t: Time Slot

Structural Properties of *MILP1*

- **Strong NP-Completeness of *MILP1.***
  - Desirable to develop an efficient and effective heuristic.

Theorem 1. *The decision problem corresponding to MILP1 is strongly NP-complete, even when* $R_1 \geq 1$ *and* $R_2 \geq 2$.

- **Equivalence to a model with idle time costs.**
  - Focus on a model with a simpler objective function.

Theorem 3. *MILP1 is equivalent to* $\widehat{MILP}_1$ *(where* $\widehat{MILP}_1$ *includes cost of idle time incurred in ORs and PACUs) when* $\boxed{C_1^o > C_2^o > 0,\ C_1^o > C_1^d > C_2^d > 0,\ \text{and}\ \frac{C_1^o}{C_1^d} = \frac{C_2^o}{C_2^d}}$*, where* C_s^d *denotes unit cost of bed idle time in stage* s, $s = 1, 2$.

$$\min_{x_{isr}^t, y_{isr}^t, z_s^t, f_{is}} \underbrace{\sum_{s \in \mathcal{S}} \sum_{r \in \mathcal{R}_s} \left[C_s^d (T - \sum_{t=0}^{T-1} \sum_{i \in \mathcal{I}} y_{isr}^t) \right]}_{\text{Idletime Cost}} + \boxed{\underbrace{\sum_{s \in \mathcal{S}} \sum_{r \in \mathcal{R}_s} C_s^o h_{sr}}_{\text{Overtime Cost}} + \underbrace{\sum_{s \in \mathcal{S}} C_s^e R_s}_{\text{Amortized Capacity Construction Cost}}}$$

Optimal ORs and PACUs: Algorithm *AdaptiveASC*

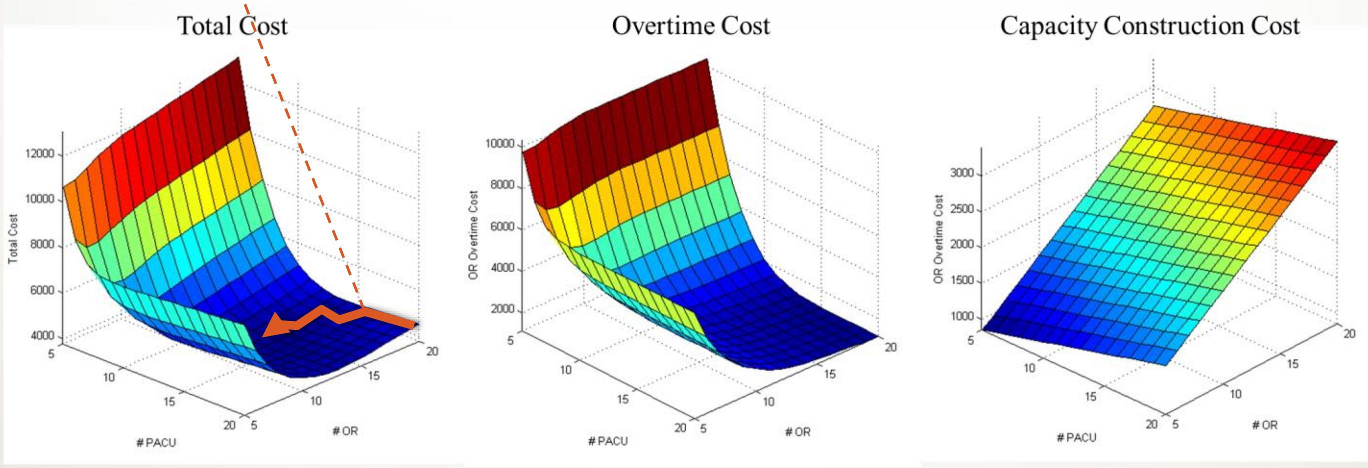
- Main Idea:
  - Under the trade-off between capacity construction cost and overtime cost,
  - **Iteratively evaluates capacity** to find the **most cost-efficient combination** of the numbers of OR and PACU.
  - Thereby, overcome the fixed capacity in HFS formulation.

Algorithm 2 *AdaptiveASC*

Input: I^w: a set of patients in weekday w, $\forall w \in \mathcal{W} = \{1, \cdots, 5\}$.
Step 0: $R_s = R_s^{UB} = R_s^{\text{temp}} = 0$, $\forall s \in \mathcal{S} = \{1, 2\}$, $\Pi' = \infty$.
Step 1: Solve Algorithm *FFP1* $\forall w \in \mathcal{W}$.
Return: $R_1 = R_1^{UB} \leftarrow \max_{w \in \mathcal{W}}\{\Lambda^w\}$, $R_2 = R_2^{UB} \leftarrow \max_{w \in \mathcal{W}}\{\Lambda^w\} + \max_{w \in \mathcal{W}}\{n_o^w\}$ where Λ^w is the number of bins from Algorithm *FFP1* and n_o^w is the number of overnight-stay patients in weekday w. $\Pi''(r) = \infty$, $\forall r \in \{1, \cdots, R_1^{UB}\}$
Step 2: Solve *MILP1* $\forall w \in \mathcal{W}$ with R_1 and R_2.
Return: $\Pi^{w*} :=$ the optimal objective value of *MILP1* in weekday $w \in \mathcal{W}$. $\Pi := \sum_{w \in \mathcal{W}} \Pi^{w*}$.
if $\Pi < \Pi'$ **then** Store the current best solution: $\Pi' \leftarrow \Pi$, $R_1^{\text{temp}} \leftarrow R_1$, $R_2^{\text{temp}} \leftarrow R_2$.
    if $R_2 > 1$ **then** Reduce the number of PACU by one: $R_2 \leftarrow R_2 - 1$. Go to Step 2.
    else
        Store the current best solution: $\Pi''(R_1) \leftarrow \Pi$, $\Pi' \leftarrow \infty$, $R_1^{\text{temp}} \leftarrow R_1$, $R_2^{\text{temp}} \leftarrow R_2$.
        if $R_1 > 1$ **then** Reduce the number of OR by one: $R_1 \leftarrow R_1 - 1$, $R_2 \leftarrow R_2^{UB}$. Go to Step 2.
        else Go to Output.
        end if
    end if
end if
Output: $\Pi^* := \operatorname{argmin}_{R_1} \Pi''(R_1)$; R_1^* and R_2^* corresponding to Π^*.

Optimal ORs and PACUs: Algorithm *AdaptiveASC*

- Illustrative example over enumerative combinations of OR & PACU
  - Algorithm *AdaptiveASC* derives optimal ORs and PACUs.



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Concluding Remarks

- **Theoretical Implications**
  - Joint capacity planning and scheduling decisions can be applied to a generic multi-stage ASC to improve the overall system efficiency.
    - Relaxed the fixed capacity assumption of traditional HFS problems.
  - Combining optimization model with data analytics can effectively deal with uncertain patient-mix and their durations.

- **Managerial Implications**
  - Practitioners can quantify the impact of changes in patient demand and various ASC business parameters on their capacity decisions.
    - Renovation or new construction.
  - Patient classification tools facilitate the applicability of the proposed capacity planning approach in practice.

Thank you!

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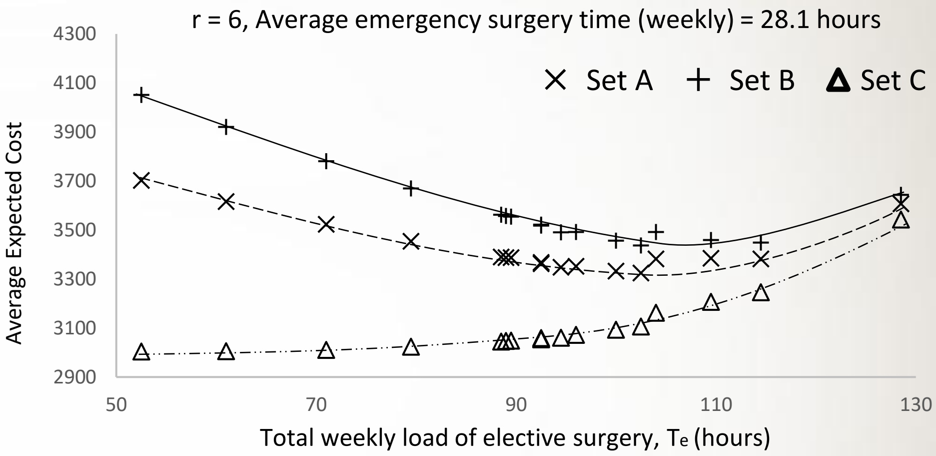
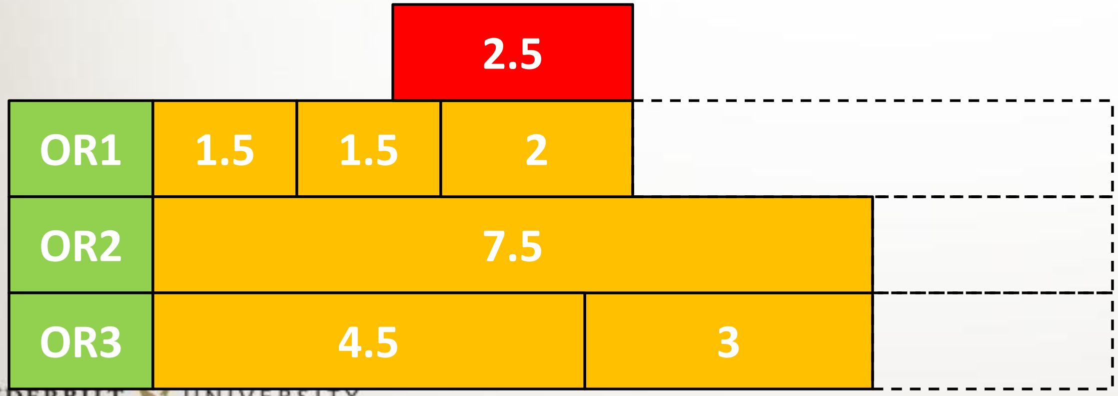
Surgery Scheduling: Research and Practice

Scheduling of surgeries is a complex process that involves simultaneous scheduling of not only several resources (staff, room, equipment, supplies, instruments), but also building flexibility in capacity-reservation policies to accommodate most types of patient classes. In the case of trauma centers this complexity increases even more due to the need for dynamic rescheduling of elective surgeries as emergency surgeries arrive randomly. In practice, these issues are tackled every day in a 'non-optimal / heuristic' way. Recent research in this area has shown the potential of implementing modified priority rules. In contrast to trauma centers, ambulatory surgery centers only perform elective surgeries and have a lower cost structure. Their profitability is therefore dependent upon efficient use of capacity. Recent research has modeled these as Hybrid Flow Shops and solved the capacity planning problem using easy to implement heuristics. This talk will also discuss some new avenues of operating room scheduling that have not yet been researched by academics.

Computational Experiments

- Weekly Average Expected cost vs Total weekly load of elective surgery





Computational Experiments

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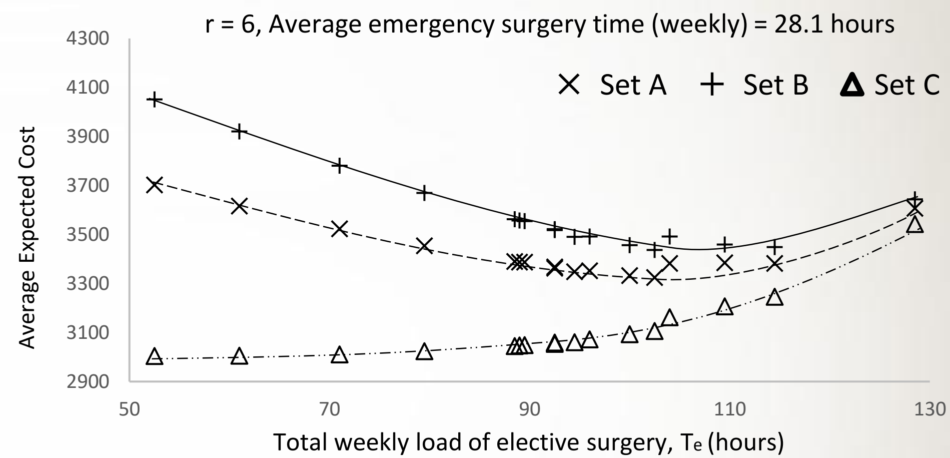

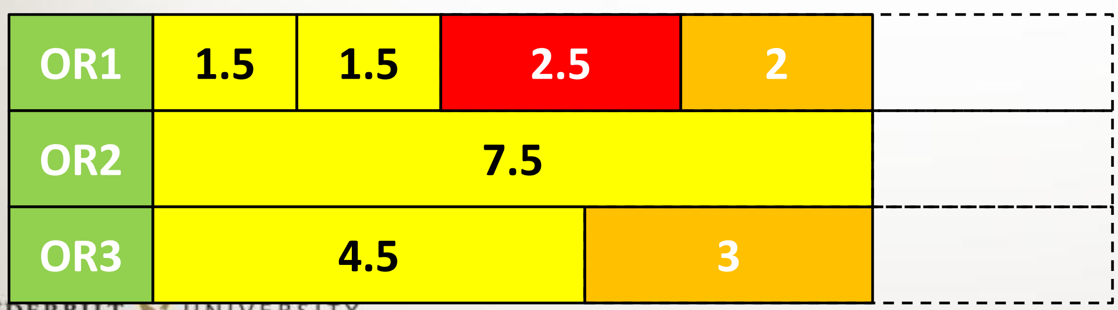

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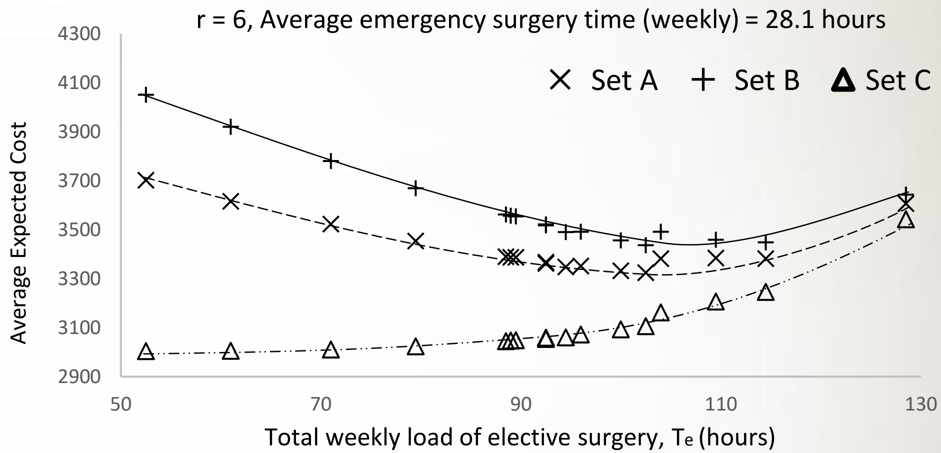

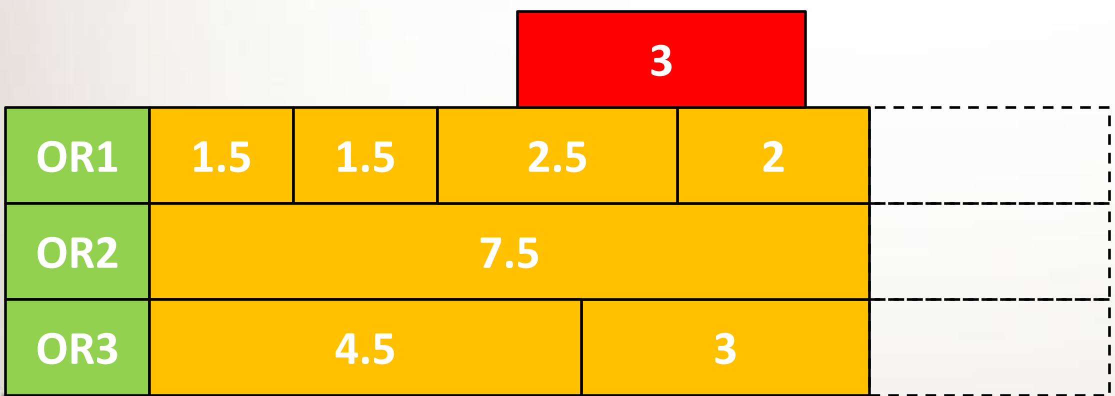

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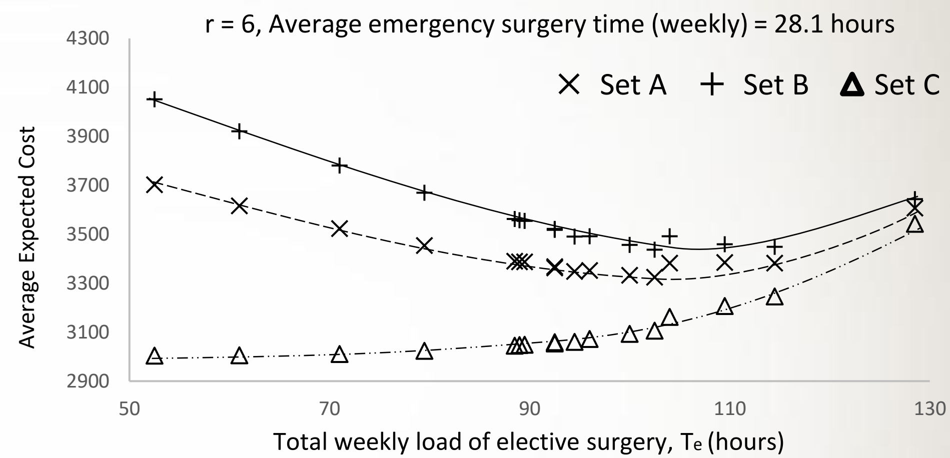
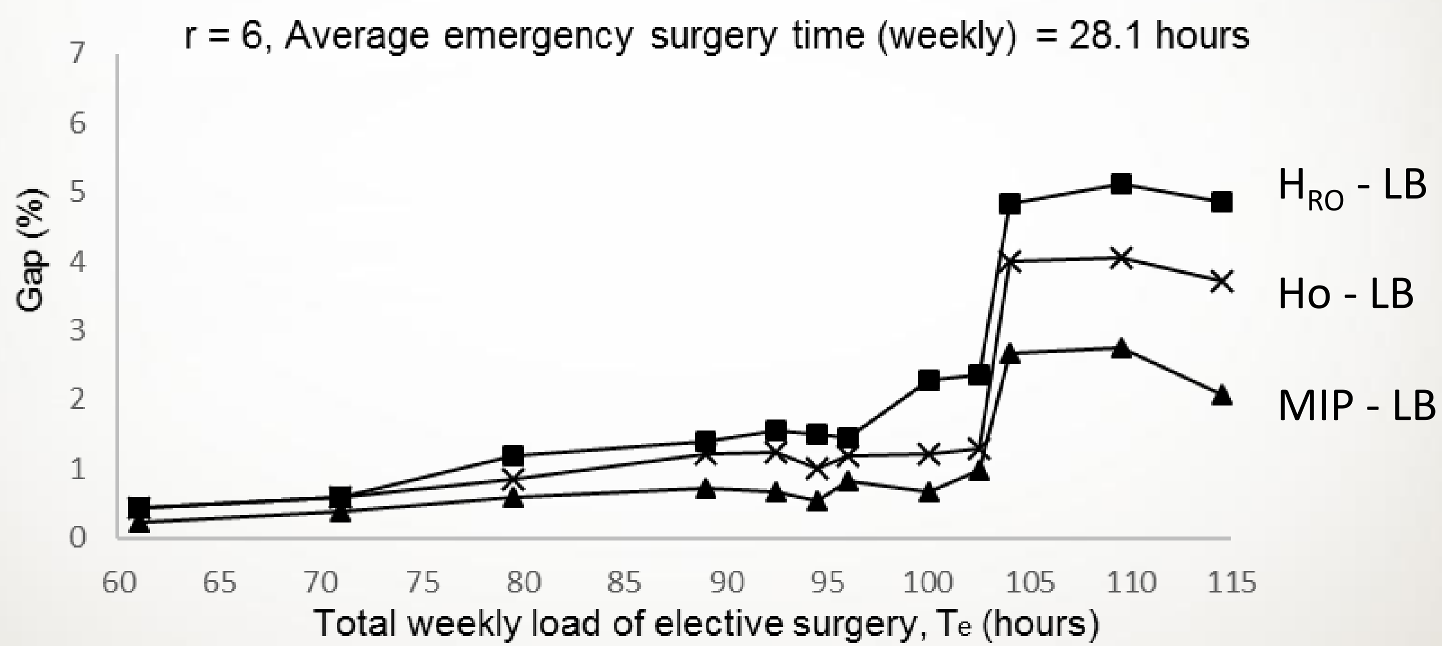


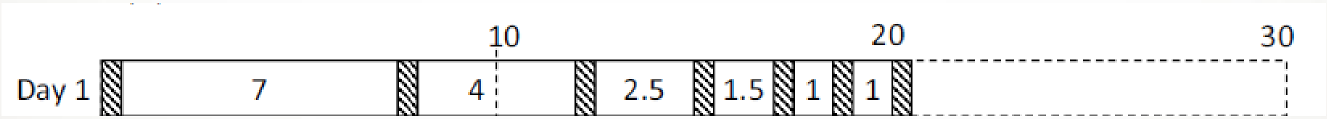
Computational Experiments

- Performance comparisons of Heuristics and MIP with respect to Lower Bound, LB.
  - Lower Bound, LB: a function of surgery times only.



Rescheduling process with Stochastic Surgery Duration

- Elective patients with Stochastic Surgery Times
  - Stochastic Heuristic
  - Based on Heuristic Online,
    - Update the surgery times for each elective patient.
    - Add the emergency patients.



Rescheduling process with Stochastic Surgery Duration

Begin

Input: A feasible schedule for surgeries in $\mathbf{S}$ from output generated by $\mathbf{H_D}$ using mean surgery times. $\mathbf{E}$ is an ordered set of emergency patients sorted by arrival times.

Initialization Step: Set current time $t = 0$.

Set subset of elective surgeries already performed or still being performed at time t $\mathbf{S_b} = \emptyset$. Set count of elective and emergency patients $N = 0$.

Set count of emergency patients $N_e = 0$.

While $(N \neq |\mathbf{S}| + |\mathbf{E}|)$ do

Step 1: At time t, use random realization of surgery times of surgeries currently being performed in ORs and find earliest available OR (denote its completion time by τ).

Set $t = \tau$. Update set $\mathbf{S_b}$ at time t.

Step 2: If any emergency patient is waiting at time t, assign the earliest arrived patient to the OR at time t, and remove this emergency surgery from $\mathbf{E}$.

Set $N_e = N_e + 1$.

Step 3: Set $\mathbf{S} = \mathbf{S} - \mathbf{S_b}$, and apply $\mathbf{H_D}$ to the remaining surgeries in $\mathbf{S}$ using their mean surgery times.

Set $N = N_e + |\mathbf{S_b}|$.

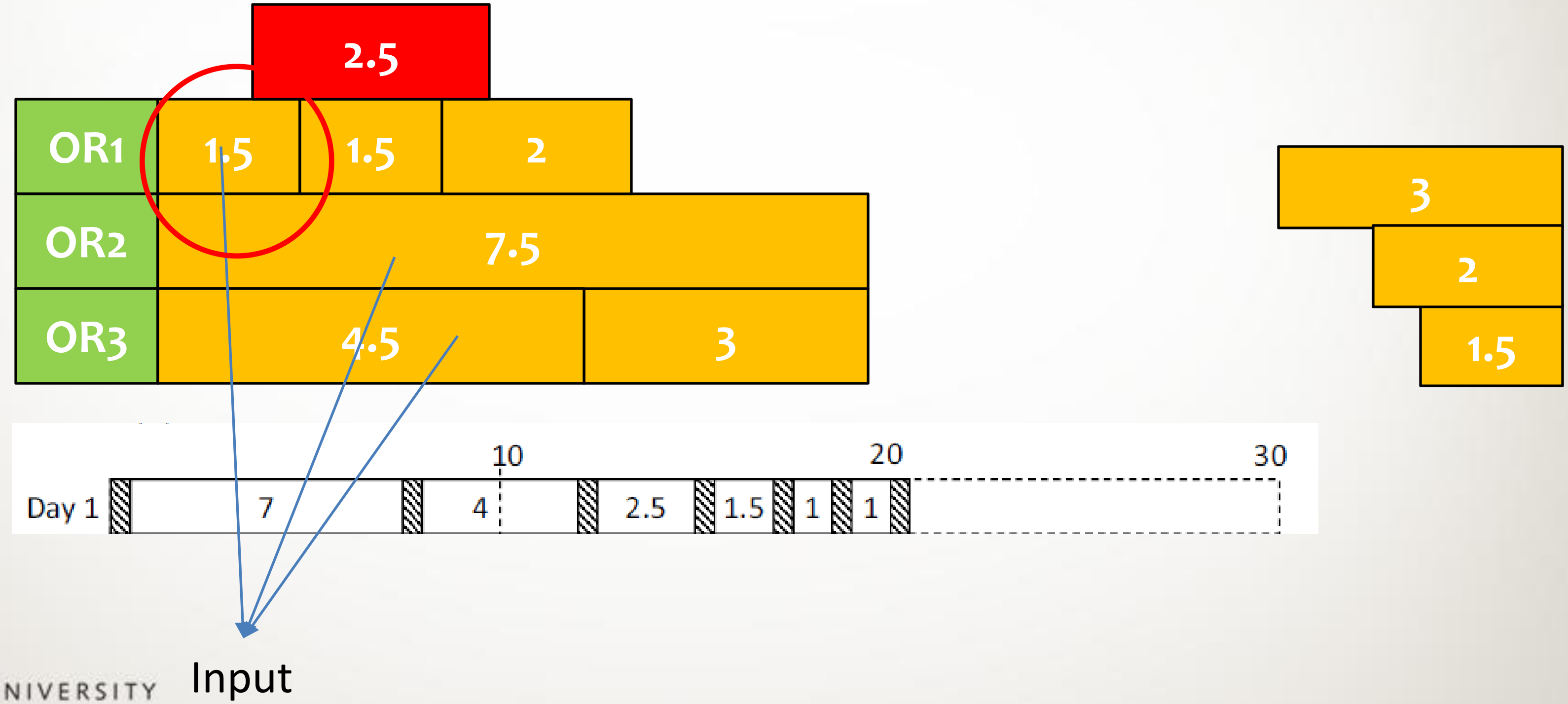
End(while)

Output: A feasible schedule for surgeries in $\mathbf{E}$ and $\mathbf{S}$ with the realized surgery times.

End

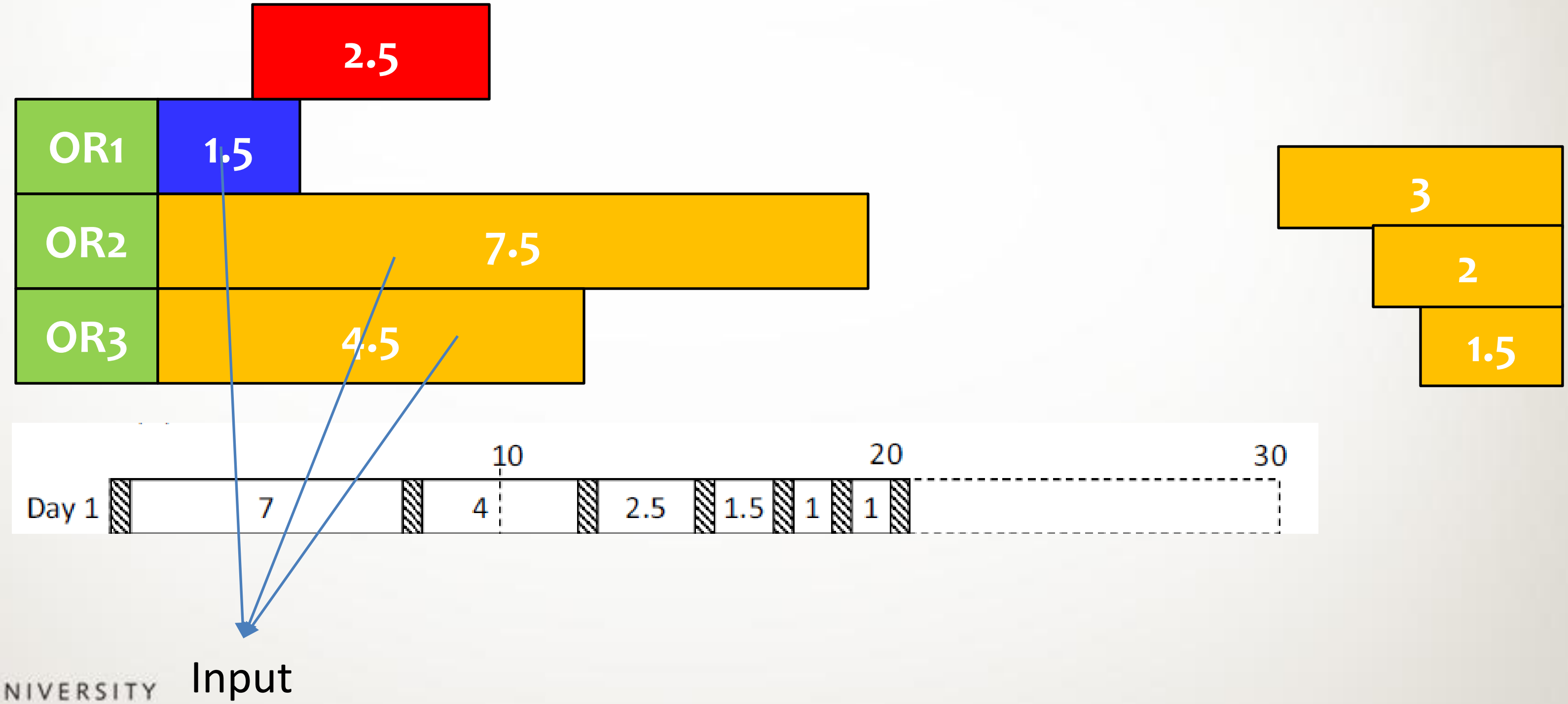
Rescheduling process with Stochastic Surgery Duration

- Actual processing time of Surgery 6 is "2.5"



Rescheduling process with Stochastic Surgery Duration

- Actual processing time of Surgery 6 is “2.5”
- At time 1.5, Surgery 6 is not completed.



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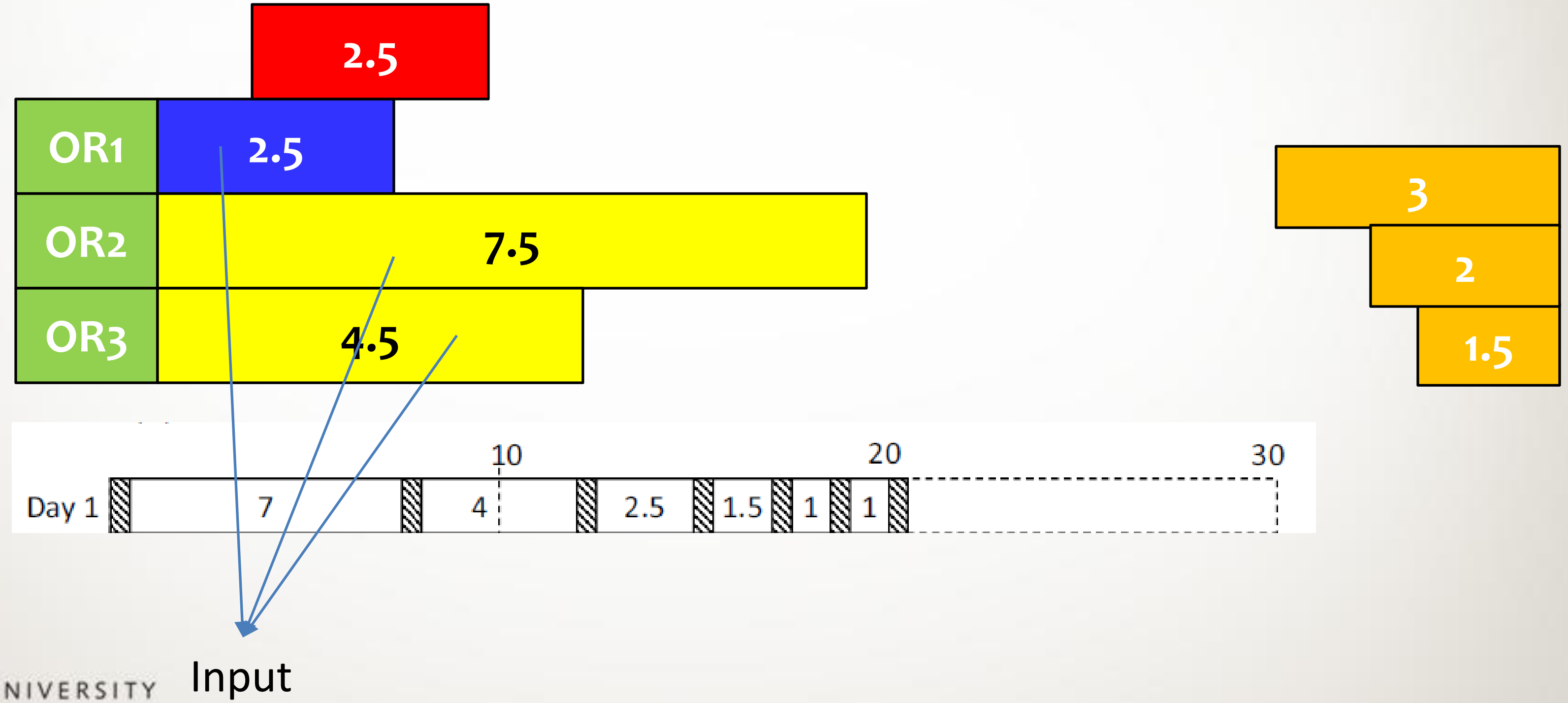

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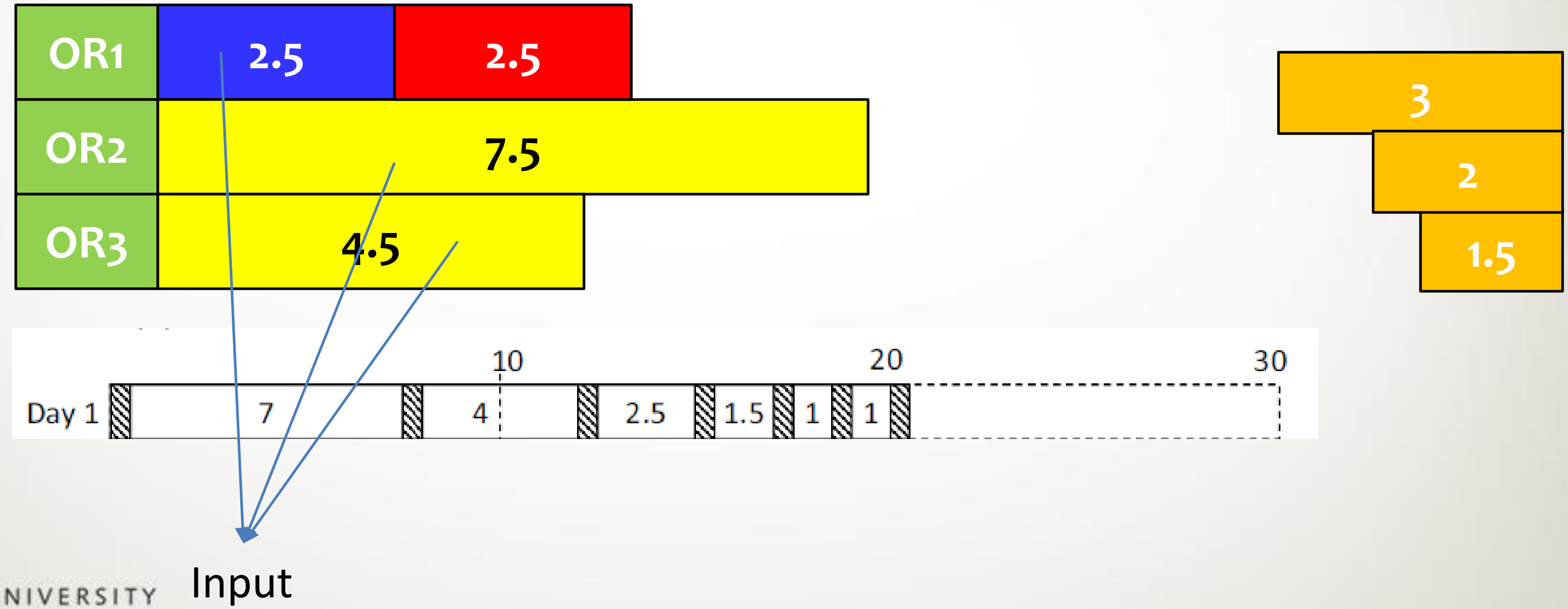

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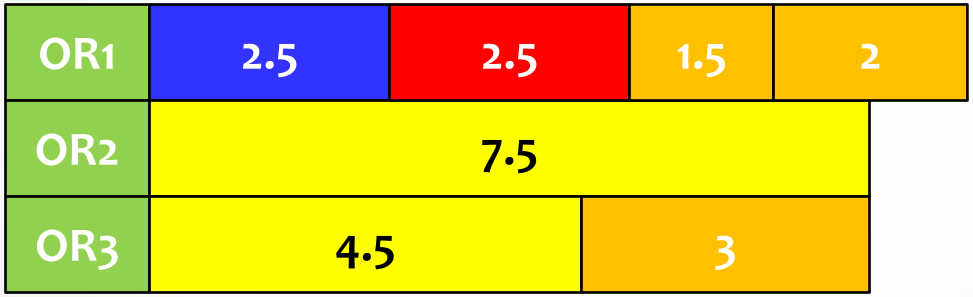

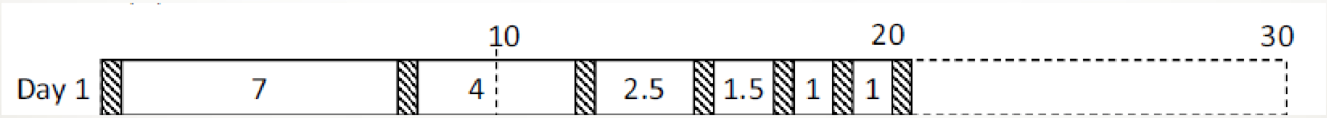

Table 2 The Position of Our Paper in Terms of Literatures Related to Scheduling and Rescheduling Procedures with Emergency Patients (Re-Sch.: Re-Scheduling; DP: Dynamic Programming; Shared BIM ORs: Shared ORs with BIM Constraints)

Reference	Shared OR	DEOR	Re-Sch.	Objective function	Optimization Approached	Other Remark
Gerchak et al. (1996)	X			Profit maximization w.r.t. overtime and surgery cancellation	Stochastic DP Model	No decision of the sequence and starting time of surgeries
Lamiri et al. (2008a)	X			Cost minimization w.r.t. overtime and regular time for elective surgeries	Heuristics with MIP	No BIM constraint; complexity status
Pham and Klinkert (2008)	X			Minimization; makespan and sum of starting times	MIP	Job shop scheduling problem; Max. waiting time constraint
Zonderland et al. (2010)	X			Cost minimization w.r.t. OR idle, overtime & surgery cancellation	Stochastic DP Model	No BIM Constraint; semi-emergency surgeries
Bhattacharyya et al. (2006)	X	X		Performance comparison between using DEORs and shared OR	Simulation Study	DEOR outperforms
Wullink et al. (2007)	X	X		Performance comparison between using DEOR and shared BIM OR	Simulation Study	Closing DEOR
Li and Stein (2008)		X		Performance measures w.r.t. overtime; waiting time for elective and emergency patients	Simulation Study	Beneficial to elective patient because of the reduced disruption of elective patients
Ferrand et al. (2014)	X	X		Performance comparison between using DEOR and shared BIM OR	Simulation Study	Using partial Flexible OR outperforms
Van Veen-Berkx et al. (2016)	X	X		Performance comparison between using DEOR and shared BIM OR	Simulation Study	Using DEOR outperforms
Gul et al. (2011)			X	Performance comparison among several heuristics w.r.t. patient waiting time and overtime	Simulation Study	No Emergency surgeries; No BIM constraint; uncertain surgery times
Erdem et al. (2012)	X		X	Cost minimization w.r.t. overtime, delay/early starting of surgery and declining emergency surgeries.	MIP	No BIM constraint; decline option
Van Essen et al. (2012)	X		X	Minimization; maximum interval between two consecutive BIM	Heuristics	Complexity status
Gul et al. (2015)			X	Cost minimization w.r.t. surgery waiting/cancellation and overtime	Stochastic MIP; Heuristics	No BIM constraint; uncertain elective surgery demand
Our Paper	X	X	X	Cost minimization w.r.t. OR operating time, idle time and overtime	MIP; Heuristics	BIM constraint; deterministic and stochastic surgery time