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PERIOPERATIVE BED CAPACITY PLANNING GUIDED BY THEORY OF CONSTRAINTS

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ABSTRACT

In most hospitals, space planning and bed capacity decisions for the various stages of the perioperative system (preoperative, intraoperative, and postoperative capacity) are made by specialized architect firms, using data supplied by hospital finance department personnel. The planners make decisions using simple rules of thumb and base their decisions on average flow-times. Facing a similar situation, and under time pressure, we showed the superiority of a simple discrete-event simulation model: one that accounted for variability in flow-times, as opposed to traditional decision-making that is based on average times. The simulation model's logic was guided by the Theory of Constraints, which enabled focusing on the key issue – how many pre- and post-op beds are needed if all the Operating Rooms work at full capacity. Under some assumptions, our simulation output showed that there was already sufficient pre-op and post-op bed capacity, thus preventing the hospital from undertaking expensive capacity expansion.

1 INTRODUCTION

Bed and resource capacity planning decisions in most hospitals are made for individual units (Green, 2005) (for example, intensive care unit, medical wards, etc.) without fully accounting for the impact this change in capacity would have on patient flows in the downstream or upstream units. Capacity design decisions are usually guided by rules of thumb that are established by architectural design firms and hospital finance departments - for example, 1.5 post anesthesia care unit (PACU) beds for every operating room (OR). Such myopic decisions are known to be suboptimal from a systems perspective. Although the superiority of systems design concepts over unitary design analysis are well established (Ackoff, 1971, 1994; Ackoff, Ackoff, Addison, & Carey, 2010), few organizations are able to do this effectively (Ackoff, 2006). This inability does not stem from an unawareness of systems thinking, but rather from an incomplete understanding of how to conceptually link the different units from an operational perspective.

We used concepts from the Theory of Constraints (Goldratt, 1990) to link patient flows between the 3 stages of the perioperative arena – the preoperative (pre-op), intraoperative (intra-op) and postoperative (post-op) units, thus operationalizing the systems thinking approach to perioperative capacity planning.

2 BACKGROUND

Financial and competitive considerations drove our organization to consider consolidating ambulatory surgeries that were spread over 3 geographically dispersed sites into one standalone 11 room operating suite (hereafter referred to as ASC). Ambulatory surgeries from the largest site (MOR) were to also move to the ASC, freeing the MOR to concentrate on longer duration and more complex surgeries. Each of these two sites have their own pre-op and post-op locations.

Capacity decisions between ASC and MOR would differ on account of patient flow patterns and patients' duration of stay at the different stages of the perioperative process. The typical patient in the ASC flows sequentially between these three stages, entering and leaving the system the same day; whereas, in the MOR, the typical patient stays for multiple nights post-surgery. Surgical case duration in ASCs are much shorter than a typical surgery in the MOR. The shorter duration of surgeries in the ASC, especially when compared to patient's length of stay in its pre- and post-op areas, is the key driver influencing administrators' calculation of bed capacity for the different stages. Capacity mismatch between stages is evidenced by 'OR on Hold' because post-op is full; or ORs are starved even when the pre-op is full. Both are symptoms of improperly conceptualized system designs.

The decision to consolidate all ambulatory surgeries to the ASC would lead to reconfiguration of surgical services among the ASC and MOR and it raised the following concerns, (1) whether the ASC, which currently performed 2.5 cases/day/OR (comprised of a mix shorter and longer duration cases), would be able to handle the anticipated increase in volume of 5 to 8 cases/day/OR (of what would be primarily only shorter duration cases in the future state), and, (2) whether the pre- and post-op stages of the ASC had enough bed capacity to handle the case volume without excessive patient waiting-times.

The ASC has 23 pre-op beds, 12 post-op beds and 11 ORs. Additionally, on average 14 of the pre-op beds were used for 23-hr observation of many patient types (afternoon admits kept overnight). These observation patients reduced the effective capacity available in the morning in the pre-op area to between 9 and 11 beds. This implied that the ASC's pre-op area would either need more beds to effectively start all the 11 ORs in a timely manner in the mornings, or the number of observation patients that were slept overnight in the pre-op would have to be reduced. Either of these decisions would entail capital expenses for the hospital. Figure 1 depicts the patient flows and capacity interdependence.

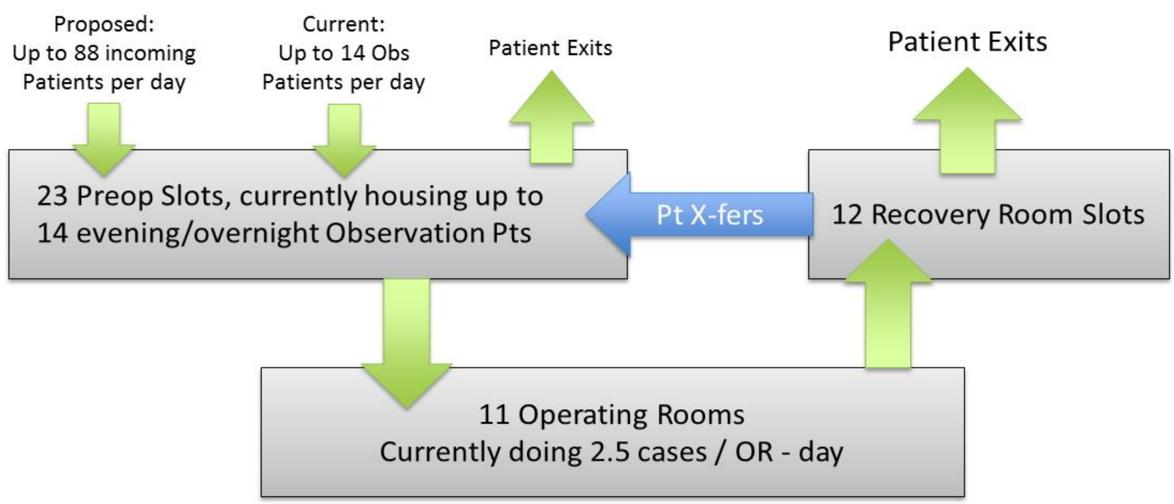

Figure 1: Current and proposed patient flow in the perioperative arena comprised on 11 Operating Rooms.

Another complexity that was making the capacity determination decision challenging was the flexibility of bed capacity between pre/post-op stages. Although not recommended from a patient experience perspective, post-op area could be used in the mornings for patient's pre-OR workup, effectively acting as an extended pre-op area. Similarly, patients that were in the last phase of their recovery post-surgery, could complete their recovery in the pre-op area. This interchangeability of roles between these stages further complicated the bed capacity calculation. Finally, uncertainty in patient length of stays at various stages made the administrators rely on average times as the basis for making calculations about these capacity decisions. Figure 2 is a high-level view of the problem.

Ideally, based on physical space and capital funds availability, the pre/post-op bed capacity decision should be the first decision made. This decision should then act as a constraint for the maximum surgical case volume possible, as well as the 'surgical services allocation between sites' decision. Following these decisions, block assignment decisions should be made and then the day-of-surgery scheduling decisions – making this a hierarchical capacity planning framework for managing OR capacity (Guerriero & Guido, 2011; Olivares, Terwiesch, & Cassorla, 2008). However, the question we faced was not what the optimal allocation of surgical services should be between the ASC and MOR, but rather, for the already decided services allocation *was there enough pre/post-op bed capacity*?

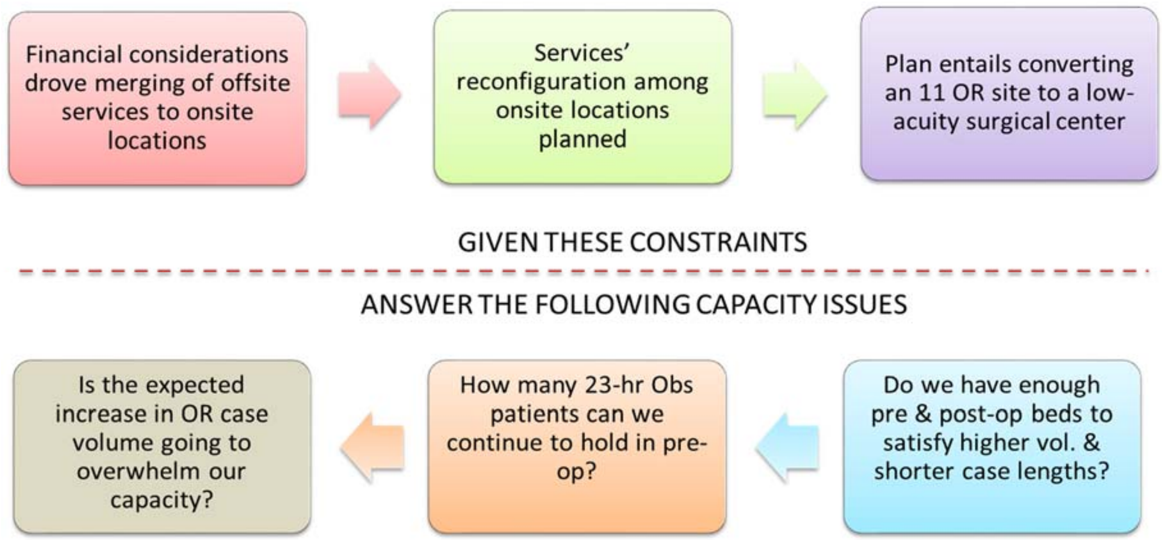

Figure 2: Pictorial depiction of the problem background and questions facing the hospital administration.

3 METHODS

3.1 Conceptual Model for the Simulation

To address the question – whether there was enough pre/post-op bed capacity in the ASC to accommodate the anticipated increase in surgical volume, and being under time-pressure for a quick answer, we realized that a full blown simulation that included detailed block allocation, staffing policies and full mix of procedure portfolio for each surgical service was not feasible in a timely manner. We therefore conceptualized the patient flow among the 3 stages of the ASC as a Simple Assembly Line Balancing problem (Boysen, Fliedner, & Scholl, 2007), where the pre- intra- and post-op stages are the workstations with strict precedence constraint and patients are jobs the move between these stages.

Further, using systems thinking guided by the Theory of Constraints (Dettmer, 1997), we argued that the pre- and post-op bed capacities are dependent upon the rate at which the ORs operate. In well-designed perioperative systems, throughput should only be constrained by the OR and not by pre- or post-op capacity.

This allowed us to reduce the simulation logic to the *pull system* concept, with OR being considered the limiting resource and pulling the cases from pre-op. Thus, next cases were assumed to be ready for the OR as soon as the prior cases exited from the OR (after allowing for a 30 minute turnover of the OR) – that is, the ORs are never starved. Similarly, we assumed that there was always a post-op bed available to *pull* the patient out of the OR as soon as the intra-op portions ended – that is, the ORs are never blocked. In other words, we wanted to test the stress on pre/post-op capacity when all the 11 ORs were at maximum flow. Therefore, the reframed question became - *"if the ORs were kept running at their maximum capacity how many pre/post-op beds would be needed at the different times of the day"?*

3.2 Simulation Data

For simulation, time duration distributions for pre-op, intra-op and post-op were created from historical data. Although time durations differ based on a patient's surgical procedure (for example, orthopedic procedure of labrum repair after shoulder dislocation differs in length from a breast biopsy with reconstruction), we were able to identify a modified Triangular distribution that fitted well for all surgeries that were anticipated to be done in the ASC. Triangular distributions had face validity and were easier to interpret for the various stakeholders. As a further validation, we vetted the parameters for the single modified Triangular distribution (one each of the three stages) with clinical experts. Table 1 lists the input parameters.

DISCRETE-EVENT SIMULATION MODEL'S INPUT PARAMETERS

Table 1: Modified Triangular distribution used as input distributions for all 3 stages of the perioperative arena simulation. Distribution parameters are values for: Min, Most Likely, Max, Percentile for the Left Tail threshold value, Percentile for the Right Tail threshold value. For example, patients' time in pre-op was modeled as being most likely = 60 minutes, with only 10% of patients staying less than the minimum time of 40 minutes, and 10% of the patients staying in the pre-op longer than 90 minutes.

	Perioperative Stage		
	Pre-op	**Intra-op**	**Post-op**
Input Distribution	Triangular(40,60,90,10,90)	Triangular(40,60,80,10,90)	Triangular(60,90,180,25,99)

Two simulation models were created based on the maximum anticipated volume (88 cases/day) and the most likely case volume (44 cases/day). As stated previously, in the current state the ASC does about 30 cases/day. This volume was anticipated to go higher immediately to about 44 cases, and even higher eventually. Since our objective with the simulation was to ascertain the stress-limit of the ASC, we considered a likely scenario (44 cases) and an extreme scenario (88 cases).

1. Scenario1: 88 cases per day
   a. Inputs: 88 time distributions (1 for each patient) for each of the 3 stages (preop-, intraop- 7 postop-) = *264 inputs*
   b. Outputs: number of patients occupying a bed in 15 minute time buckets from 5 AM to 7 PM, for the 3 stages = 14 hours * 4 buckets of 15 minutes each * 3 stages = *168 outputs*
2. Scenario 2: 44 cases per day
   a. Inputs: 44 * 3 = *132 inputs, b)* Outputs: same as Scenario 1 = *168 outputs*

3.3 Simulation Model

The simulation model was created in MS-Excel using the add-in @Risk 6 for Excel (Palisade Corp). 5 replications, each with 10000 iterations were conducted. The model's logic, using the 88 case scenario, is described in Figure 3. Output collected was the number of patients in each 15 minute time bucket from 5:00 AM to 7:00 PM in each of the 3 phases. The statistics collected for this primary metrics were the Minimum, Maximum, Mean, 5^{th} and 95^{th} percentiles. Figure 4 gives a sample snapshot of the statistics for the combined number of patients in 7 different 15-minute time buckets. Outputs were collated and then displayed in one comprehensive chart.

Discrete-Event Simulation Model Logic

Scenario 1 – 88 cases/day (8 cases per each of the 11 ORs)

Intra-op

1. For each of the 11 ORs, generate a string of 8 intra-op times from the Triangular distribution ($t^{n}_{s,r}$, where *s* = stage (pre- intra- or post-op), *r* = room number (1 to 11), *n* = patient count (1 to 88).
2. Assume 1st case of the day enters the OR at 7:30 am.
3. 1st case end time = 7:30 am + $t^{n}_{s,r}$ =$end^{n}_{s,r}$
4. 2nd case enters OR time = 1st case end time + 30 minutes for set up = $start^{n}_{s,r}$
5. Repeat steps 3 and 4 for all 8 patients in each of the 11 ORs

Pre-op

6. Assign pre-op exit time for the 1st case for each of the 11 ORs as 7:30 am
7. For each subsequent case calculate pre-op exit time as, $end^{n}_{s=pre-op,r}$= $start^{n}_{s=intra-op,r}$
8. Generate 8 strings of pre-op time from pre-op's Triangular distribution ($t^{n}_{s=pre-op,r}$)
9. Calculate pre-op enter time for each case as, $start^{n}_{s=pre-op,r}$ = $end^{n}_{s=pre-op,r}$ - $t^{n}_{s=pre-op,r}$
10. Repeat steps 8 and 9 for all patients

Post-op

11. Assign post-op start time for each case as, $start^{n}_{s=post-op,r}$= $end^{n}_{s=intra-op,r}$
12. Generate 8 strings of post-op time from post-op's Triangular distribution ($t^{n}_{s=post-op,r}$)
13. Calculate post-op exit time for each case as, $end^{n}_{s=post-op,r}$ = $start^{n}_{s=post-op,r}$ + $t^{n}_{s=post-op,r}$
14. Repeat steps 12 and 13 for all patients

Figure 3: simulation model's logic and sequence in which random events are generated. The model is built around the concept that the maximum capacity ever needed in pre-op and post-op would occur when all the 11 ORs work at their full capacity, as the ORs are the constraining resource in the perioperative system.

Name	Cell	Graph	Min	Mean	Max	5%	95%
Range: TotalHR+PACU							
TotalHR+PACU / 07:46_08:00	AR249	-2 14	0	6	13	4	9
TotalHR+PACU / 08:01_08:15	AS249	2 20	3	11	19	7	14
TotalHR+PACU / 08:16_08:30	AT249	6 26	8	16	24	13	20
TotalHR+PACU / 11:16_11:30	BF253	10 35	11	22	32	17	26
TotalHR+PACU / 11:31_11:45	BG253	10 35	11	22	31	18	26
TotalHR+PACU / 11:46_12:00	BH253	10 30	11	21	29	16	25
TotalHR+PACU / 12:01_12:15	BI253	5 30	7	18	27	13	22

Figure 4: Snapshot of the key statistics collected for the combined number of patients occupying a bed in either pre-op or post-op by time of the day segmented in 15-minute time buckets. Output was collected for 168 15-minute time buckets (5:00 AM to 7:00 PM). For example, between 7:46 am and 8 am, on average there are 6 patients in the pre-op and post-op stages combined, and there are never more than 13 patients.

4 RESULTS

Using the simulation model we first proved that the traditional way of determining bed capacities using deterministic techniques based on average time duration would be woefully inadequate. Deterministic modeling would assume that each patient occupied pre-op, OR and post-op for exactly the same amount of time. This would give spurious results. Using the simulation model, but using deterministic times, we showed that the results would dramatically differ based on the values chosen. Figure 5 gives the output for two such situations. The top frame in the figure is built with patients' pre- and intra-op time of 60 minutes and post-op time of 90 minutes; the bottom frame represents the scenario where the patients stayed for 60 minutes in each stage. Both of these estimates seemed reasonable for the ASC and many experts agreed with this. The output shows that if the first-frame situation were to occur, then the current post-op bed capacity (of 12 beds) would be overwhelmed, as periodically there would be a need to bed 22 post-op patients. However, in the second frame situation, the existing capacities would be enough, and even the existing volume of observation patients that sleep overnight in the pre-op area would be easily accommodated.

This simple analysis proved the need for a conducting a simulation analysis with stochastic input times, and for making decisions not based on averages but on the complete distribution of outputs.

Figure 6 gives the collated results of the simulation of Scenario 1 (88 cases/day) – the maximum volume possible scenario to stress test the system. The chart gives the 5th and 95th percentile of the number of patients at the pre/post-op stages, as well as the combined sum. At 95th percentile of OR flow, 12 beds of post-op capacity is insufficient, as the post-op would need 16 beds; however, moving late-stage recovery patients into the pre-op beds later in the day ensures sufficient total beds to keep the ORs running at full tilt. This is feasible, because later in the day pre-op just needs 12 beds at the 95th percentile to keep the ORs running at full-tilt. So even after accounting for some late-discharge observation patients, the pre-op can easily spare 4 beds to accommodate late-stage recovery patients from the post-op.

Moreover, since up to 14 patients from the previous day stay overnight as observation patients in the pre-op beds, it became clear that to achieve full operational potential of the ORs, the pre-op area requires up to 14 of its 23 beds available to start the morning. That is, pre-op should house no more than 9 observation patients overnight (as opposed to the typical 14 that it was currently doing), and these should move out early to make room for new post-op patients. Figure 7 gives the collated results for the simulation of Scenario 2 (44 cases/day) – the most likely scenario. The morning profile of the combined number of patients in the pre- and post-op stages is the same as that for Scenario 1 simulation results. The only difference is that the day starts ending earlier, which is depicted by the downward sloping profile of the number of patients in the system starting in the afternoon, as opposed to later in the evening, which is what happens in Scenario 1. The inferences about number of beds needed in the pre-op in the morning hours still remains the same.

5 DISCUSSION

Surgical services' reconfiguration among different sites of our medical center created a need to evaluate capacity levels at the various stages of the perioperative arena. Of main concern was the capacity at the pre-op and post-op stages in the future-state ambulatory surgical center (ASC). In the current state, this site had sufficient capacity because it handled a mix of short and long duration cases. The intermingling of longer duration cases buffered the pre-op and post-op stages from operating in a high throughput environment. The capacities at these two stages were therefore adequate in the current state. However, in the future state, the ASC would have only shorter duration cases in the OR, this would necessitate the pre-op and post-op stages to keep pace with the high throughput ORs. This raised the concern that the current capacity of the pre-op and post-op stages may not be adequate.

We show that a deterministic approach based on average length of stay would have led to erroneous capacity planning for both the pre- and post-op areas. Using a discrete-event simulation model of patient flows through the three stages of the perioperative arena in the ASC, we helped predict the magnitude of operational risk to the perioperative system caused by bed shortages arising from the planned service reconfigurations. Conceptualizing ORs as the limiting resource simplified the simulation logic to "what pre/post-op capacity maximizes OR capacity"?

Simulation output from both the most-likely scenario (44 cases/day) as well as the extreme scenario (88 cases/day) showed that the existing capacities at the pre-op and the post-op stages were adequate under the following operational policies: (1) since the pre-op has 23 beds, and at the 95^{th} percentile up to 14 beds may be needed in the pre-op at the start of the day, no more than 9 observation patients should be housed overnight in the pre-op beds. In the current state, on average 15 observation patients slept overnight. Finding an alternate bed in the hospital for 6 observation patients would not be too difficult. Without the simulation models' results, the administration was planning on building additional beds to accommodate observation patients; however, the simulation output showed that the pre-op area can still accommodate most of the overnight observation patients. (2) In case the ASC volumes exceeds expectations (and tends towards the high-volume scenario of 88 cases/day), the post-op stage will be constrained for capacity (16 beds needed at the 95^{th} percentile as opposed to the current bed capacity of 12). However, starting in the early afternoon, late-stage recovery patients can be moved to the pre-op stage, as the pre-op stage doesn't need more than 12 beds in the late afternoon even at the 95^{th} percentile.

The service reconfiguration occurred in Nov-2014 when the future-state ASC became operational. ASC's daily case volume has ranged between 40 and 55 cases. To manage patient flows on higher volume days, operational leaders follow the policies outlined above, and have never felt congested or overwhelmed. Observation patients sleeping overnight in the pre-op area have ranged between 9 and 14, and a Nurse Practitioner helps ensure timely discharge (internal target is 11 am) in order to have pre-op beds available for late-recovery post-op patients. The hospital therefore did not have to add any additional beds or staffing.

Simulation results thus influenced capacity and staffing decisions, and guided the high-stakes negotiations among the surgical services. The results helped the administration evaluate the tradeoffs when making decisions under uncertainty.

Systems redesign – such as pre-op and post-op bed and staff capacity planning, risks failure if the well-established concepts of capacity management, and models that factor uncertainty in patient flow times, are not explicitly considered. In this work, conducted prior to a desired service reconfiguration among different sites at our institution, we showed the superiority of a stochastic discrete-event simulation model that is guided by the operational concepts of systems thinking and guided by a pull system over a deterministic model that is based on average times and guided by rule of thumb.

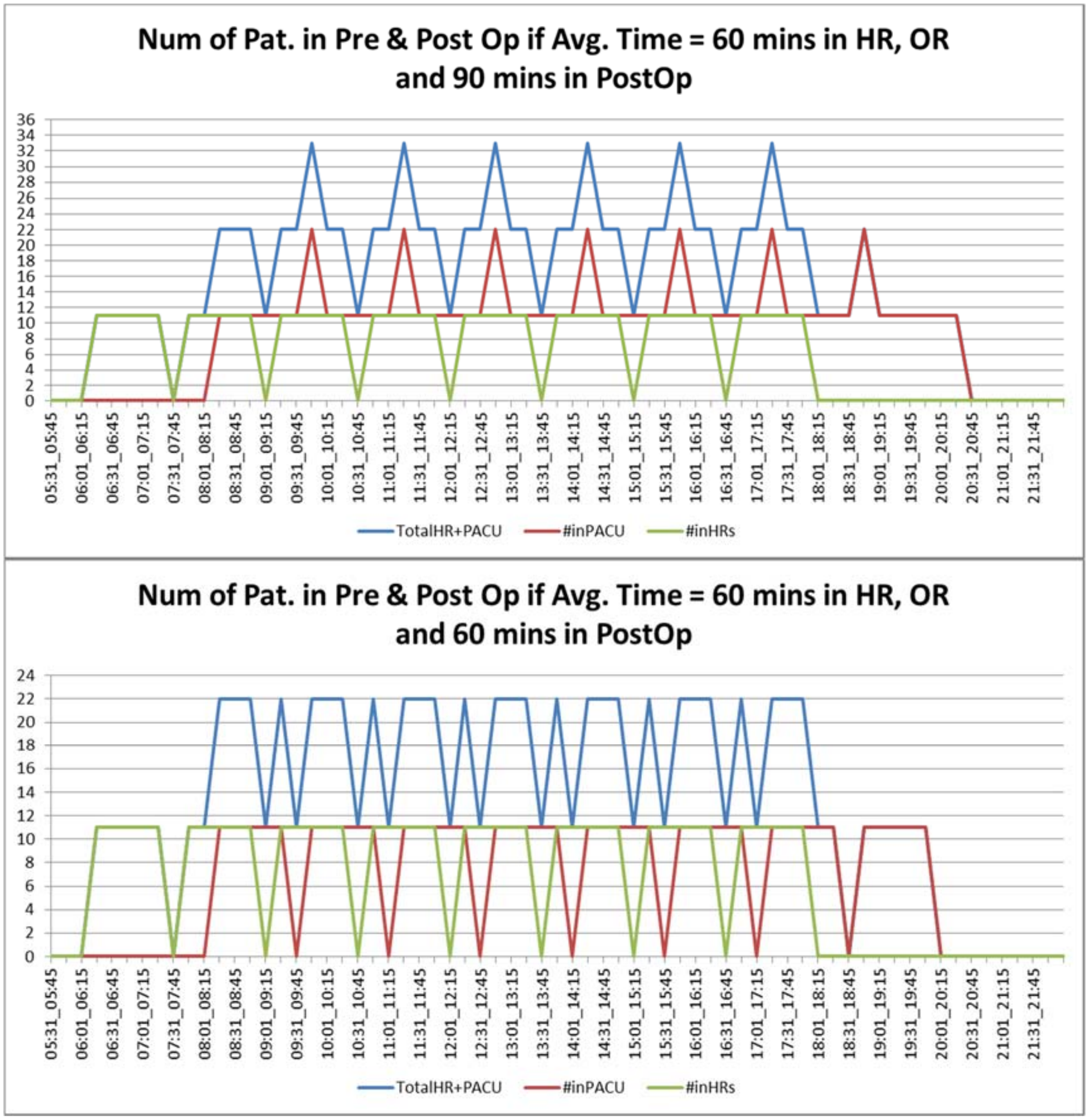

Figure 5: Number of patients in the pre/post-op stages individually and combined under two hypothetical situations where patient flow times are deterministic. Inference about post-op beds needed differ significantly between the two situations, highlighting the inadequacy of using averages and underlining the need to conduct simulations considering stochasticity on inputs and outputs.

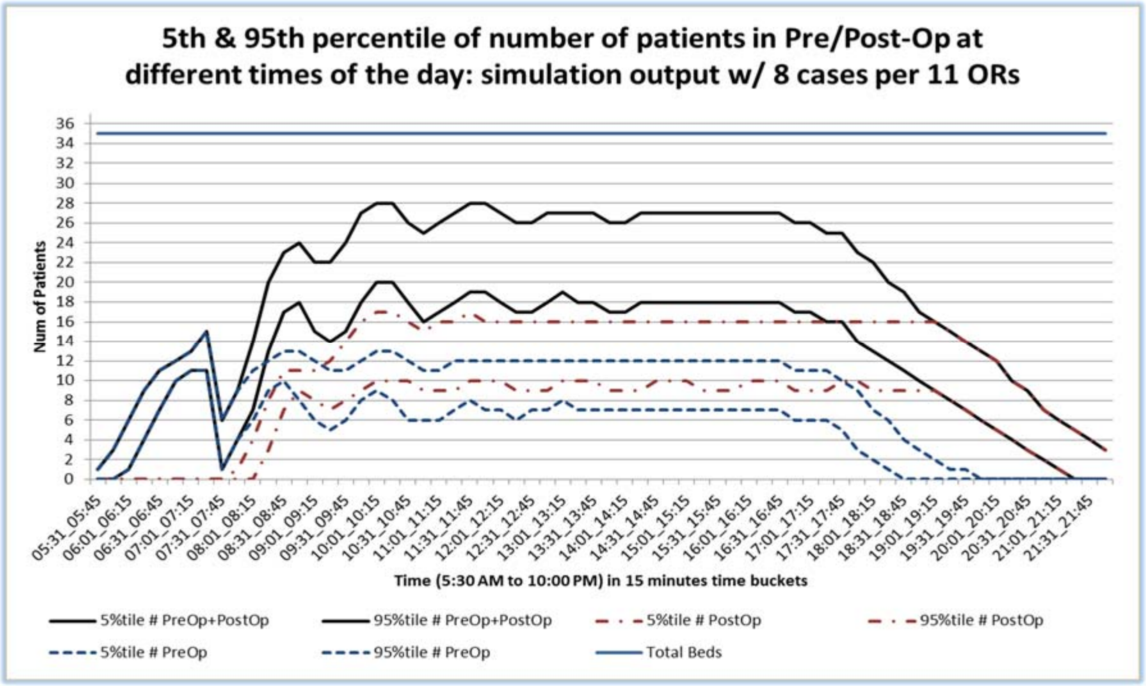

Figure 6: Simulation output of number of patients at pre/post-op stages by time of the day if all the 11 ORs operated at full capacity and had 8 cases/day.

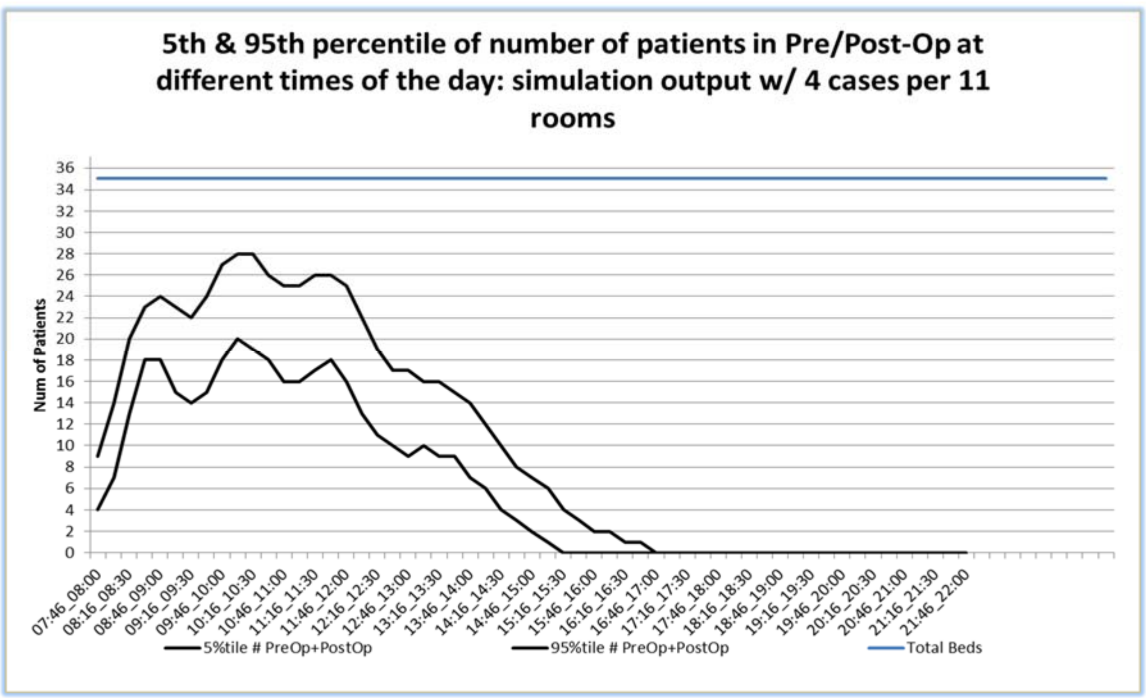

Figure 7: Simulation output of number of patients at pre/post-op stages by time of the day if all the 11 ORs operated at full capacity and had 4 cases/day.

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