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Evaluating the Generalizability of an Approach to Improve the Inpatient Day-of-Discharge Process

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Abstract

Research has suggested that emergency department boarding and crowding can be alleviated via improvements to the inpatient discharge process. Recently, a conceptual model was developed to model the inpatient day-of-discharge process and validated at a local hospital. In this study, we evaluate the generalizability of this conceptual model to a Neurology unit at a different hospital. We further test if a recently proposed target discharge strategy would benefit this unit. Using real data from the Neurology unit, we show that the conceptual model is robust and generalizable to this unit even though substantial differences in the patient population and system parameters exist. Additionally, the n-by-T strategy, especially 2-by-noon, yielded over 11% reduction in upstream boarding time and over 14% advancement in the discharge completion time. Our findings suggest that such generalizable models for modeling discharge processes and a target strategy such as n-by-T will likely have wider adoption and implementation in the inpatient units at other hospitals.

Keywords
Discharge planning, simulation, inpatient modeling, n-by-T, discharge targets

1. Introduction

Emergency departments (EDs) in the US are becoming increasingly common as general access points for acute care admissions. Consequently, ED boarding (patients waiting in the ED for inpatient beds) and crowding are becoming more apparent and impactful problems. Several studies have suggested that improving the inpatient discharge process to better balance discharges with admissions can alleviate ED capacity issues [1,2,3].

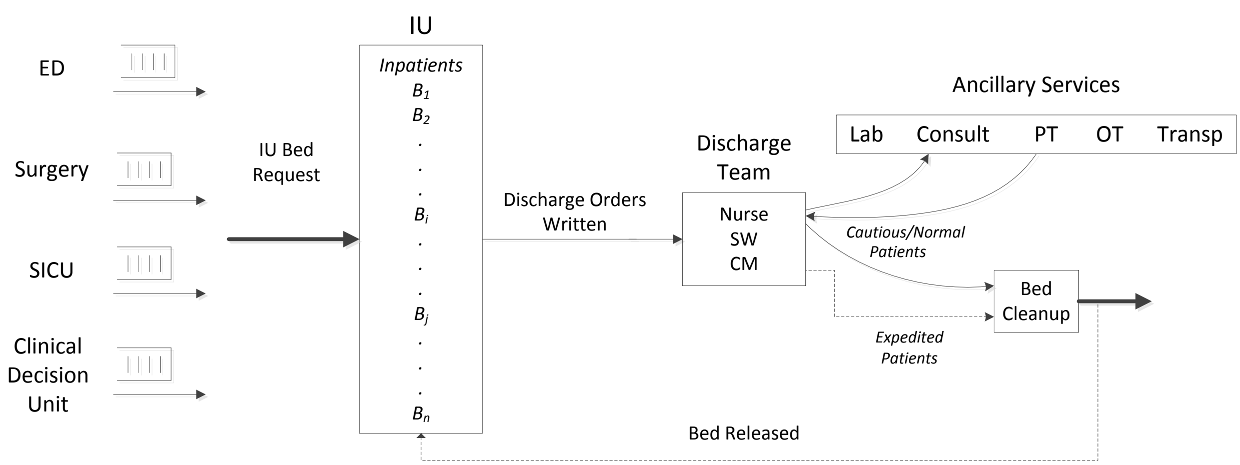

Figure 1: Schematic of an Inpatient Discharge Process

As demonstrated in Figure 1, on a typical day in an inpatient unit, requests for beds in the unit arrive from multiple upstream sources. Most beds in the unit are occupied by inpatients; thus, in order for an incoming bed request to be fulfilled, a discharge must occur to free up an inpatient bed. The unit will typically have a few patients already identified to be discharged on this day (referred to as the day-of-discharge). For each of these patients, multiple processes must be completed, such as a discharge order placement by their physician, discharge instructions communication, and medications fulfillment. Upon completion of the discharge, the bed and room must be cleaned by hospital environmental services before the bed can be occupied by an incoming patient. Thus, it is apparent that discharge efficiency is critical, not only for patients to be discharged but also for patients waiting in upstream units.

A few studies exist that examine analytical methods to evaluate inpatient discharge strategies and their potential effects on inpatient units and upstream patient boarding. Wong et al. built a system dynamics simulation model which suggested that smoothing out inpatient discharges over the course of a week reduces the number of ED beds occupied by general internal medicine inpatients and also reduces ED length of stay (LOS) [4]. Powell et al. used a simplified spreadsheet-based daily model and demonstrated that better timing of discharges should substantially reduce admitted patient boarding (across ED, elective surgery, and ICU transfers) [5]. Ozen et al. constructed a hospital-wide simulation model and found that prioritizing discharges in units with longer admission queues offered the most reduction in patients waiting to be admitted, rather than focusing on earlier discharges across all units [6]. Matis et al. developed an optimization model, along with a proposed discharge process redesign, to determine an optimal discharge target time for each patient on a unit, given both patient and system centric constraints [7]. Parikh et al. recently proposed a novel day-of-discharge strategy, *n*-by-*T*, as a target for inpatient units to advance discharge completion times and reduce upstream boarding. This strategy was initially tested using a simulation model and later pilot at a trauma inpatient unit at a local hospital in the Midwest US [8].

In this paper, we address the following questions: *(i) Could a recently proposed model for the inpatient discharge process be generalized to units at other hospitals?* and *(ii) Would the n-by-T strategy offer similar benefits at those units?* We consider a Neurology inpatient unit at a hospital in the Northeast US to address the above questions. We first briefly summarize the general (conceptual) model (presented in [8]) to capture the relationship between inpatient discharges and upstream patient boarding (Section 2), following by a discussion of its application at this Neurology unit and the evaluation of the *n*-by-*T* strategy (Sections 3 and 4).

2. A General Model for the Day-of-Discharge Process

Although the typical day on an inpatient unit is quite complex, the processes associated with discharges for that day and the corresponding new admissions can be viewed, in the general sense, as two separate streams (discharge ready patients and bed request arrivals), linked by the resource of inpatient beds, as demonstrated in Figure 2.

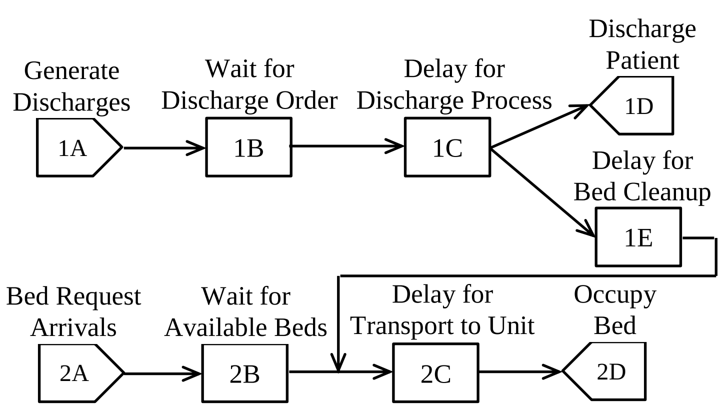

Figure 2: Schematic of the General Model

The first stream, the number of patients (entities) to be discharged (block 1A), depends on the unit's daily discharge rate. These patients when discharged at the end of the day will empty the beds they are currently occupying. Depending on the occupancy rate in the unit, it may be important to make available additional empty beds at the start of the day; 0 if 100% occupancy. In a typical unit, discharge-ready patients wait until their discharge order is placed (block 1B), after which they are delayed for some discharge process length (block 1C). After this, the patients are discharged (block 1D) releasing the beds they had occupied, which would need cleaning before the bed becomes available (block 1E).

The second stream, the patients requesting a bed, are generated throughout the day based on the unit-specific arrival process (block 2A). These requests enter a queue of beds (block 2B). Once a bed becomes available, a requesting patient in the queue (based on FIFO or priority) would experience a transportation delay (block 2C) before reaching the room and occupying the empty bed (block 2D).

This general model requires inputs for the following: (i) number of discharges per day (block 1A); (ii) discharge order placement times (block 1B); (iii) discharge process lengths (block 1C); (iv) bed cleanup delays (block 1E); (v) bed request arrival times (block 2A); (vi) transport to unit delays (block 2C). The outputs of the model are (i) discharge completion times of day (block 1D); (ii) upstream patient boarding times (difference between block 2A and block 2D). Note that the boarding time includes transportation delay, often the way a unit records it; the true boarding (waiting time) would exclude this transportation delay.

This general model makes several assumptions: all processes associated with the discharge are combined into one delay; discharge order placement is used as a proxy for discharge initiation; the model delays for bed cleanup and for transport incorporate both the time spent waiting for these services to arrive and the actual service time. However, as shown in [8] and as we show below, these assumptions appear reasonable to capture the critical dynamics in the unit. We embedded this general model in a simulation framework in AnyLogic v7.2.

3. Application of the General Model to a Neurology Unit

We now discuss the application of this general model to the Neurology unit in the Northeast US to obtain evidence of the generalizability of it beyond the Trauma unit in Midwest US. The key differences observed in the Neurology unit (vs. Trauma) are as follows: (i) there are 26 inpatient beds (vs. 21) with an average discharge time of day of 2 p.m. (vs. 4 p.m.); (ii) the average upstream boarding was 3.53 hr (vs 2.41 hr) and the rate of discharges was 3.57 patients/day (vs 4.91). So clearly, besides patient populations, the values of the system variables are disparate.

The above data for the Neurology unit was obtained after 30 hours in job shadowing unit nurses and obtaining a year's worth of retrospective data for all patients discharged from the unit in 2015. For these patients, we obtained four date-time stamps from the electronic health records: (i) bed request placed; (ii) in room time; (iii) discharge order placed; and (iv) discharge completion time. Although these four time stamps were specific to the same patient encounter, we considered the arrival data independently of the discharge data in our analysis and subsequent model.

For each patient, we considered the bed request and in room times for only the first time the patient arrived on the unit; if the patient was temporarily transferred to other units throughout their course of treatment and then returned to the Neurology unit, we did not use the bed request and in room times when they returned to the unit, as we were modeling only new incoming demand for unit capacity. We only considered records for patients who were eventually discharged out of the hospital from the Neurology unit. We excluded records with missing values and records with chronologically inconsistent data (in room time occurring before bed request placed, or discharge completed before order placed). Because we modeled only the day of patient's discharge, the length of stay was not considered. Additionally, we only considered records for patients who arrived in the room the same day their bed request was placed and patients who were discharged the same day their discharge order was written. Figure 3 summarizes the bed request arrivals, discharge order placements, and discharge completion times from this final dataset, by hour of day over 1303 records.

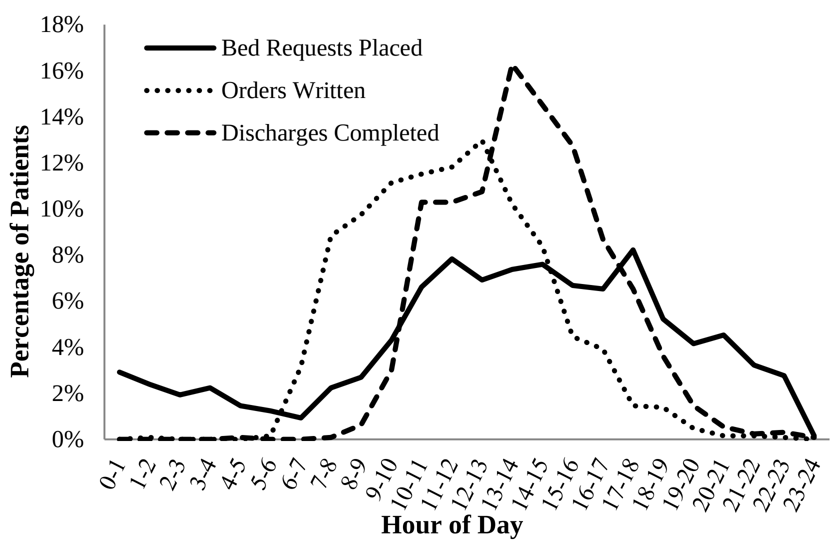

Figure 3: Bed Requests and Discharges at the Neurology Unit in 2015

From the four time stamps provided in the dataset, we derived input distributions for the model for the following four inputs: (i) number of patients discharged per day; (ii) discharge order writing time of day; (iii) discharge process length (the difference between discharge order placed and discharge complete); (iv) bed request arrival time of day. Unfortunately, we were unable to obtain any data directly for bed cleanup times; for these, we relied upon expert estimates and simulation model feedback. Likewise, for transportation to the unit times, we had only sparse, incomplete data, so we relied upon a combination of this data and simulation model validation feedback to derive appropriate distributions. Because of the difficulty in quantifying the unit's daily occupancy rate due to ongoing room renovations and temporary bed unavailability, we assumed 1 extra empty bed at the start of a day.

Table 1: Model Inputs Derived from the Neurology Unit Data in 2015

Model Input	**Distribution**
Number of patients to be discharged (per day)	Poisson(3.57)
Time discharge orders placed (hour of day)	Normal 2 Mixture: Normal(8.27,0.99); probability 0.19 Normal(12.32,2.66); probability 0.81
Discharge process length before 10 a.m. (hours) between 10 a.m. and 4 p.m. (hours) after 4 p.m. (hours)	 Weibull(3.998,1.75) Weibull(2.21,1.52) Weibull(1.24,1.73)
Bed cleanup duration (hours)	Normal(1.51, 0.12)
Arrival of bed requests from upstream units	Non-stationary Poisson process (rate varies by hour of day); daily avg 3.57
Transportation to unit length before 7 a.m. (hours) between 7 a.m. and 7 p.m. (hours) after 7 p.m. (hours)	 Triangular(0.34,0.86,1.7) Triangular(0.16,1.49,4.46) Triangular(0.16,0.83,2.15)
Number of empty extra beds at start of day	Constant = 1

Table 1 summarizes the final input distributions corresponding to the Neurology unit. We observed multiple instances of non-stationary processes (by time of day) at this unit. Such processes were often longer (larger means, longer tails) the earlier they occurred in the day, indicating perhaps that units are typically busier in the mornings catching up with work accumulated from overnight, or else there is less of a focus on discharges in the morning.

We averaged our simulation findings over 1,000 replications (of a 24-hour day-of-discharge on the unit). For validation, we compared the simulation outputs against the unit's actual data: on the inpatient discharge side, discharge completion time of day; on the upstream bed request side, patient boarding time (length). As shown in Table 2, our simulation model output reasonably matched our retrospective unit data for both validation measures, across multiple statistical measures.

Table 2: Model Validation against Data from the Neurology Unit

Outcome	**Measure**	**Actual Data**	**Simulation**
Discharge Completion Time of Day	N (Patients/Days)	1303/365	3608/1000
	Mean (hr)	13.99	14.01
	Median (hr)	13.92	13.90
	Std Deviation (hr)	2.54	2.75
	Skewness	0.27	0.09
	95% CI on Mean (hr)	[13.85,14.13]	[13.92,14.10]
Boarding Time	N (Patients/Days)	1303/365	3500/1000
	Mean (hr)	3.53	3.74
	Median (hr)	2.60	2.58
	Std Deviation (hr)	2.90	3.36
	Skewness	1.84	1.76
	95% CI on Mean (hr)	[3.37,3.69]	[3.63,3.85]

Clearly, the general model (summarized in Section 2) seems to fairly accurately model the Neurology unit's day-of-discharge process. This is now the second, distinct, unit where such a general model was validated, the first being the Trauma Unit [8]. The two successful validations of the general model across differing units indicate that, while a unit-specific model can capture detailed dynamics, the majority of the inpatient unit admission and discharge process dynamics may be common across units and could be modeled in a unit-independent framework to generalize findings.

3. Generalizability of the *n*-by-*T* Target Discharge Strategy

The second research question was if the previously proposed *n*-by-*T* target inpatient discharge strategy [8] would benefit the Neurology unit as well. Essentially, the *n*-by-*T* strategy proposes a target number of patients, *n*, to be discharged from the unit by a target time of day, *T*. These *n* patients are to be selected by the unit from among the patients already identified as ready to be discharged on this particular day. In a sense, this strategy is a hybrid of two separate strategies considered earlier; advancement in discharge order writing time and reduction in discharge process length. The key benefit of the *n*-by-*T* strategy is that it offers the advantage of requiring order writing advancement and discharge process length reduction efforts for only a fraction of discharge-ready patients on a given day. This potentially avoids excessive workload on unit staff in the morning (working on *all* discharge-ready patients vs. a fraction of them), while still achieving the goal of better synchronization between discharges (bed availability) and upstream bed request arrivals (bed demand) via earlier discharges.

Figure 4 displays the expected effect of several specific instances of the *n*-by-*T* strategy on discharge completion times at the Neurology unit. The bimodal nature of the distribution of discharge completion times results from the *n* patients discharged earlier in the day, and the rest are discharged per the current process, though at a reduced volume. Note that while the distributions for *n*=1 and *n*=2 are different, there is only a marginal change when *T* changes for a given *n*, indicating that the number of patients is the critical factor to be decided when selecting a variant of *n*-by-*T* for the unit, rather than the time of day by which to discharge these patients.

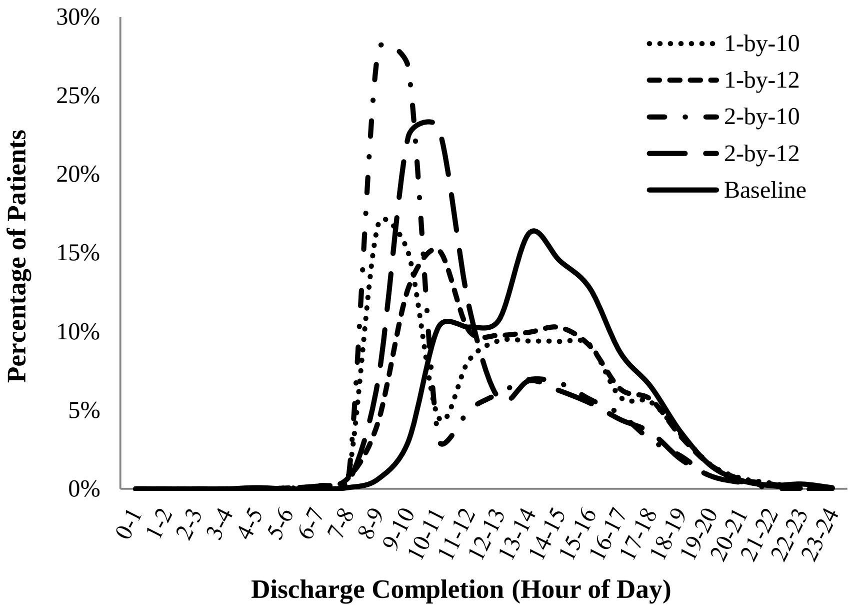

Figure 4: Discharge Completion Times for Various *n*-by-*T* Strategies

We quantified the estimated benefits of implementing the *n*-by-*T* strategy at the Neurology unit using four measures. For upstream patients, we calculated the percent reduction in average boarding time per patient; correspondingly, we calculated the estimated increase in upstream unit capacity in the form of annual upstream bed hours (based on 1303 discharges). For inpatient discharges, we calculated the percent advancement in average discharge completion time of day per patient; likewise, we calculated the corresponding estimated increase in inpatient unit capacity in the form of annual inpatient bed hours. These results are summarized in Table 3. The numbers displayed are the averages of 10 simulation runs of 1,000 replications each.

Table 3: Predicted Outcomes of n-by-T at the Neurology Unit

	% Reduction in Average Boarding Time per Patient		**Increase in Annual Upstream Bed Hours**		**% Advancement in Average Discharge Completion Time of Day per Patient**		**Increase in Annual Inpatient Bed Hours**	
	***n*=1**	***n*=2**	***n*=1**	***n*=2**	***n*=1**	***n*=2**	***n*=1**	***n*=2**
***T*=10**	7.59%	13.57%	349	624	9.58%	18.31%	1747	3338
***T*=11**	7.46%	12.70%	343	584	8.53%	16.38%	1555	2987
***T*=12**	5.60%	11.63%	258	535	7.55%	14.75%	1377	2688

It is apparent that, while all combinations of *n* and *T* experimented in our study offer improvements over the current system across all four metrics, *n* has much more of an effect than does *T*. Additionally, the most aggressive strategy, 2-by-10, results in the largest improvements in all four areas; intuitively, this is to be expected.

These conclusions were also found in the study at the Trauma unit [8]. The expected benefits due to *n*-by-*T* were larger at the Trauma unit, however ~11% for the 1-by-*T* strategies and ~15% for the 2-by-*T* strategies. This is possibly due to the higher patient volumes at the Trauma unit and/or their later peak discharge time of day. That study also identified several potential difficulties to successful implementation of *n*-by-*T*, such as identification of the *n* patients, timely completion by the consulting physician, disposition-specific complications, and the need for feedback, education, and sustainment. Such considerations would be vital if such a target strategy were to be implemented at the Neurology unit.

4. Discussion and Conclusion

The main contribution of this study was to obtain evidence of the generalizability of a proposed model for the inpatient day-of-discharge process. To do this, we considered a Neurology unit at a large hospital system in the Northeast US. Despite the differences between the units in the initial study and this current study (e.g., trauma vs neurology, geographical location, system parameters), we were able to successfully validate the general model at the Neurology unit as well by only altering the input distributions specific to the unit, without any change in the model's logic. This provides evidence that the model is robust and generalizable, as demonstrated across two different units in two different hospitals; however, we recommend further studies to verify this claim.

We also observed that the *n*-by-*T* target strategy would provide similar benefits to this Neurology unit as well. Although the expected boarding time reductions were not as large for this unit (e.g., for 2-by-noon, it was over 11% vs. 15% at the Trauma unit), the general conclusions remained the same: all combinations of *n* and *T* offer improvements over the current system across four different metrics, with more aggressive strategies offering the most improvements, and with *n* having a much larger effect on the expected benefits than *T*. This suggests that *n*-by-*T* may be an effective discharge target strategy for any unit in any hospital; again, further research at other units is recommended to truly generalize the benefits of this target strategy.

Future research in this area should consider the inclusion of the differences among the discharge-ready patients based on the underlying effort required by the unit staff to discharge them on that day, disposition location, and capacity limitations at care transition locations.

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