Improving Emergency Department patient throughput by considering providers' inpatient admission rates

a mathematical programming approach

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Scheduling Emergency Department doctors' work shifts by aligning their practice patterns to patient arrival patterns may alleviate crowding in the *inpatient unit*. This increases bed availability for admissions, thereby relieving ED crowding.

ABSTRACT

We propose a new policy for improving Emergency Department (ED) throughput that does not rely on provider behavior change. ED crowding is an international problem resulting in adverse clinical outcomes, access disparity, and financial losses.

Previous studies have sought to improve throughput by increasing allocation of ED beds or other resources. Some have identified the impact of providers' efficiency on throughput, but none have considered admission rate as a factor. Studies have shown that increasing inpatient bed allocation improves ED throughput, but have not considered that ED providers control patients' flow to inpatient beds via admission orders. Individual providers vary in these decisions.

When providers who tend to admit more patients are scheduled on days of the week that are naturally busier, crowding may result as more patients occupy ED beds while awaiting another service, blocking new patients. Admitted patients boarding in the ED increase all ED patients' lengths of stay. Research shows that on average patient outcomes are the same regardless of admission decision. Providers have multiple reasons, many unrelated to outcomes, for admitting more patients, e.g. lower risk tolerance, malpractice fear, level of experience. ED boarding *is* associated with worse outcomes.

We use mathematical programming to test schedules with high, medium, and low admitters to find the configuration that leads to the most beds available on the most impacted day of the week.

MODEL

INTEGER PROGRAM

Decision variable:

x_{ij} admission rate per day of week

Definitions:

$i = \{1 \dots 7\}$ day of the week

$j = \{l, m, h\}$ admission rate: low, med, high

E_i ED arrivals

$A_i = \sum_{j \in \{l,m,h\}} (E_i * x_{ij} * j) \ \forall \ i$ inpatients admissions from ED

I_i inpatient admissions, not from ED

$N_i = A_i + I_i \ \forall i$ total new inpatients

α proportion of patients with LOS ≥ 2 days

β proportion of patients with LOS $= 3$ days

B inpatient bed count (optional)

$C_i = \alpha N_{i-1} + \beta N_{i-2} \forall \ i \geq 3$ inpatient census (Wednesday – Sunday)

$C_2 = \alpha N_1 + \beta N_7$ (Tuesday)

$C_1 = \alpha N_7 + \beta N_6$ (Monday)

$Z = \min_{i \in 1 \dots 7} (B - C_i)$ minimum # of beds available across week

Objectives:

$maximize \ Z_b$ best case

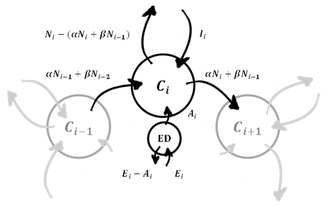
$minimize \ Z_w$ worst case

Subject to:

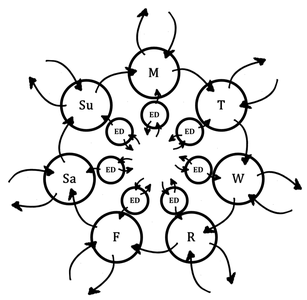
$$x_{ij} \in \mathbb{B} \ \forall \ i, j$$

$$\sum_{j=l}^{h} x_{ij} = 1 \ \forall \ i$$

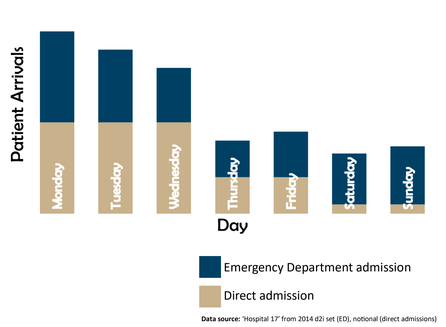
$$\sum_{i=1}^{7} x_{i,\mathrm{l}} = \sum_{i=1}^{7} x_{i,\mathrm{h}}$$



Transition state diagram



Weekly inpatient admissions (mean)

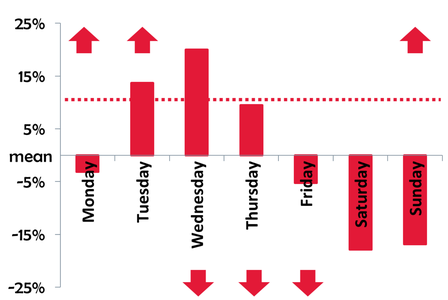


Data source: 'Hospital 17' from 2014 d2i set (ED), notional (direct admissions)

Patterns exist in inpatient arrivals. Patients are admitted to inpatient units either directly or via the ED. Patients are discharged directly from inpatient units and from the ED. Admitted patients typically stay more than one day in the inpatient unit (data from Children's National Medical Center (CNMC): roughly 40% one day, >60% two or more days). Typically Mondays and Tuesdays are the busiest days in EDs, with a dip late in the week and a slight increase on weekends. Elective surgeries, the largest driver of direct admissions, typically happen near the beginning of the week, and rarely on weekends. These two patterns together heavily front-load the week.

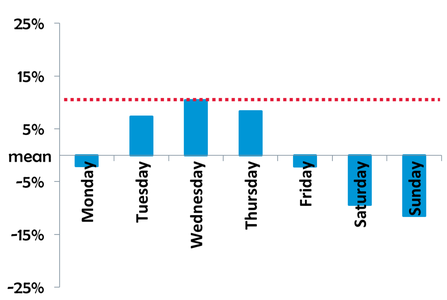
RESULTS

'Worst' scheduling configuration



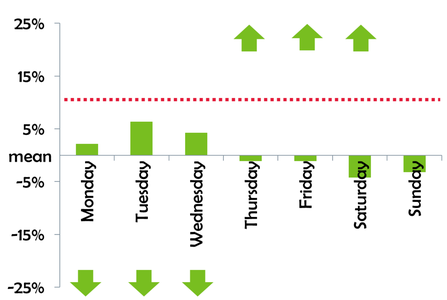
Rate	22%	22%	18%	18%	18%	20%	22%
high	1	1					1
med						1	
low			1	1	1		

'Chance' scheduling configuration

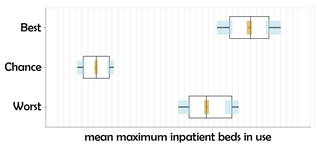


Rate	20%	20%	20%	20%	20%	20%	20%
high							
med	1	1	1	1	1	1	1
low							

'Best' scheduling configuration



Rate	18%	18%	18%	22%	22%	22%	20%
high				1	1	1	
med							1
low	1	1	1				



NEXT STEPS

Using Discrete-Event Simulation we will verify our model, include stochasticity, and experiment with specific hospitals' data. (The SMORE plot, left, from the CNMC model reinforces that there is no 'one size fits all' solution.) Enumerating 393 viable configurations is trivial. Scan the QR code for more!

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