Emergency Department (ED): The Case for Service Engineering

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Service Engineering can be described as the "design, analysis and management of services, fusing ingredients from Operations Research, Statistics … and even more" (Mandelbaum, 2007).

Our focus here is on patients flow data from an Emergency Department (ED) at one of the largest hospitals in Israel. The data analysis motivates the development of new models that, in turn, enhance our understanding of the physical behavior of the service system and help in making relevant managerial decisions.
Background on “Anonymous” hospital

- 1,000 inpatients beds (hospitalized simultaneously).
- 75,000 patients are hospitalized annually.
- The ED attends to about 250-300 patients daily, with 58% classified as Internal patients and 42% classified as Surgical or Orthopedic patients.
- The ED contains three major areas:
  1) Internal acute.
  2) Internal walking.
  3) Trauma.
Emergency Department physical structure

Background
Patient Flow - ED’s Activity Resource Chart

Background

Alternative Operation - C
Recourse Queue - Synchronization Queue -
Ending point of alternative operation -
Data available (patient resolution, 4 years)

- Admission Time.
- Discharge Time.
- Sub Unit ID (Internal / Surgical / Orthopedic / Trauma).
- Birth Date (Age).
- Gender (Male \ Female \ Unknown)
- Admission Code - Patients' general cause of admitting.
- Send By Code - The authority that sends the patients to the ED.
- Send Letter - The presence / absence of an application letter.
- Complain Reason - The patient's complaint.
- Body Part - patient's body parts on which she or he complained.
- Arrival State – The state of the patient on arrival.
- Release Status – The status of departure.
- Ward
Pattern of Patients Arrivals:

Example for different time horizon decisions: Strategic, Tactical, and Operational
Arrivals to the ED - Strategic level (patients per month)

Seasonal effect? Trends?
Arrivals to the ED – Tactical level (patients per day)

January 2005

Day of the Week Impact
Arrivals to the ED – Operational level (patients per hour)
Patient Length of Stay (LOS)

(Two short examples of analysis)
LOS survival by patient type

![Graph showing LOS survival by patient type with data table showing: ED_Type | N | ALOS | Std(LOS)]

<table>
<thead>
<tr>
<th>ED_Type</th>
<th>N</th>
<th>ALOS</th>
<th>Std(LOS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int</td>
<td>265,257</td>
<td>251</td>
<td>224</td>
</tr>
<tr>
<td>Ort</td>
<td>109,721</td>
<td>153</td>
<td>190</td>
</tr>
<tr>
<td>Surg</td>
<td>67,972</td>
<td>158</td>
<td>197</td>
</tr>
<tr>
<td>Tra</td>
<td>3,962</td>
<td>141</td>
<td>170</td>
</tr>
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</table>
LOS survival by patient severity

<table>
<thead>
<tr>
<th>Severity</th>
<th>N</th>
<th>ALOS</th>
<th>Std(LOS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>436,931</td>
<td>213</td>
<td>218</td>
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<tr>
<td>ICU</td>
<td>9,008</td>
<td>133</td>
<td>156</td>
</tr>
<tr>
<td>V</td>
<td>2,948</td>
<td>211</td>
<td>180</td>
</tr>
</tbody>
</table>
Occupyancy Level
(number of patient in the ED)
Distribution of the time ED was with (L) number of occupied beds

Mean: 32.97231
Std: 14.92503
Distribution of the time ED was with number of occupied beds (L) – Per Hour of the Day
The average occupied beds – by Hour of the Day
ED: Throughput (Flow) vs. Occupancy (Human)

Congestion-Dependent Flow-Rates: Light, Regular, Heavy

- $\lambda(L)/L$
- $\mu(L)$

Patients per Day per Bed vs. L (Number of Occupied Beds)
Occupancy level – Fitting a Theoretical Model
Occupancy level – Fitting a theoretical model

From simple to complex models:

- $M/M/\infty$
- $M_t/M_t/\infty$
- Birth-and-Death: $\mu(L)$, $\lambda(L)$
- Simulation (Sinreich and Marmor, 2005)
- Poisson arrivals at $\lambda=0.138$ (patients per minute) rate.
- Infinite number of exponential servers, work at $\mu=0.005$ (patients per minute per bed) rate.
- The Steady-state distribution ($\pi_i$) is from a Poisson process ($R=\lambda/\mu$):

$$\pi_i = e^{-R} \cdot \frac{R^i}{i!}, \ i \geq 0$$

![Graph showing empirical and theoretical probabilities vs. number of occupied beds.]
Fitting a theoretical model: time varying $M_t/M_t/\infty$

<table>
<thead>
<tr>
<th>t</th>
<th>$\lambda_t$</th>
<th>$\mu_t$</th>
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<tr>
<td>0</td>
<td>0.12892</td>
<td>0.00531</td>
</tr>
<tr>
<td>1</td>
<td>0.09375</td>
<td>0.00502</td>
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<tr>
<td>2</td>
<td>0.07016</td>
<td>0.00452</td>
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<td>3</td>
<td>0.0576</td>
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<td>6</td>
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<tr>
<td>8</td>
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<td>21</td>
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<td>22</td>
<td>0.18916</td>
<td>0.00551</td>
</tr>
<tr>
<td>23</td>
<td>0.16302</td>
<td>0.00513</td>
</tr>
</tbody>
</table>
Fitting a Theoretical Model: Birth-and-Death with $\mu(L)$, $\lambda(L)$

![Graph showing empirical and theoretical data](image-url)
Fitting a theoretical model: Simulation (based on the Resource Activity Chart)
Ambulance Diversion (AD): The Consequence of Using the “Wrong Model”
Description of a paper dealing with AD

Hagvedt et al. 2009 (*Cooperative strategies to reduce ambulance Diversion*):

- Simple B&D model with constant $\lambda$ and $\mu$:

- Then use it to research cooperative strategies.
Hagvedt et al. 2009 - Models to compare with

- Model 0: Hagvedt et al. protocol ($\lambda$ and $\mu$ are constant. We use $\gamma=\lambda$ because all insured).
- Model 1: B&D process, constant $\lambda$ and state dependant $\mu$.
- Model 2: B&D process with state dependant $\mu$ and $\lambda$.
- Arena: ED simulation model.

A.D protocol:
Start block at L=54, resume at L=44
Comparing results – # “blocked patients” per month

Oneway Analysis of Number AD per Month By Model

Oneway Anova

Summary of Fit

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rsquare</td>
<td>0.743196</td>
</tr>
<tr>
<td>Adj Rsquare</td>
<td>0.739493</td>
</tr>
<tr>
<td>Root Mean Square Error</td>
<td>45.85004</td>
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<tr>
<td>Mean of Response</td>
<td>147.2972</td>
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<tr>
<td>Observations (or Sum Wgts)</td>
<td>212</td>
</tr>
</tbody>
</table>

Arena predicts more than twice than model 0
Comparing results – # minutes of AD per month

Oneway Analysis of Total Minutes at AD per Month By Model

Oneway Anova

Summary of Fit

- Rsquare: 0.016693
- Adj Rsquare: 0.002511
- Root Mean Square Error: 2513.723
- Mean of Response: 1368.427
- Observations (or Sum Wgts): 212

no statistical difference
Increase Quality of Care by Using the Simulation Model for Real-Time Staffing
Intraday staffing in real time: Objectives

- [Gather real data in real-time regarding current state]
- Complete the data when necessary via simulation.
- Predict short-term evolution (workload) via simulation.
- Corrective staffing, if needed, via simulation and mathematical models.

- All the above in real-time or close to real-time
When arrivals can be modeled by a time-inhomogeneous Poisson process, with arrival rate $\lambda(t); t \geq 0$, The **Offered Load** ($R$) is calculated as the number of busy-servers (or served-customers), in a corresponding system with an infinite number of servers (Feldman et al., 2008). For example (one station),

$$R(t) = E[\int_{t-S}^{t} \lambda(u)du] = \int_{-\infty}^{t} \lambda(u)P(S > t - u)du$$

$S$ - (generic) service time.
QED-staffing approximation aim at achieving service goal $\alpha$ (while also balancing utility level):

$$n_r(t) = R_t + \beta_t \sqrt{R_t}$$

$$1 - \alpha = P(W_q > T) \approx h(\beta_t) e^{-T \mu \beta_t \sqrt{n_r(t)}}$$

$n_r(t)$ - recommended number of resource $r$ at time $t$, using OL.

$\alpha$ - fraction of patients that start service within $T$ time units,

$W_q$ – patients waiting-time for service by resource $r$,

$h(\beta_t)$ – the Halfin-Whitt function (Halfin and Whitt, 1981),
Experiment – performance of future shift using existing staffing

**Utilization:**

- $I_p$ - Internal physician
- $S_p$ - Surgical physician
- $O_p$ - Orthopedic physician
- $N_u$ - Nurses.

**Used Resources (avg.):**

- #Beds – Patient’s beds,
- #Chairs – Patient’s chairs.

**Service Quality:**

- $%W$ - % of patients getting physician service within 0.5 hour from arrival (effective of $\alpha$).
OL method achieved good service quality: $\%W$ is stable over time.
Intraday staffing over the mid-term
Mid-term staffing: Results

%W (and #Arrivals) per Hour by Method in an Average Week ($\alpha=0.3$)
Conclusions

• First, we demonstrated how using empirical findings can help better forecast ED performance (e.g., the outcome of Ambulance Diversion policy).

• Second, we demonstrate how ED's simulation model which is used with empirical data, can support real-time and mid-term staffing, which enables the control of ED, and helps to cope with unpredictable changes in the arrival process.
Thank You