Patient Flow Analysis: Improving the Quality and Efficiency of Healthcare Delivery

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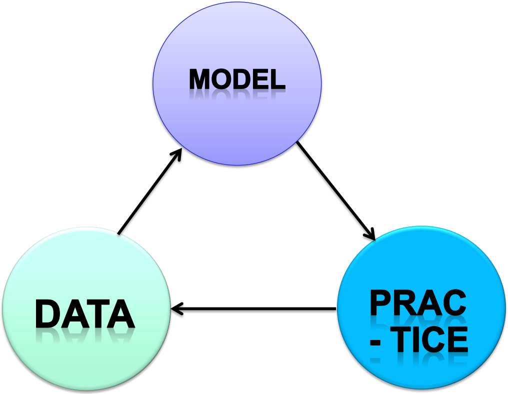
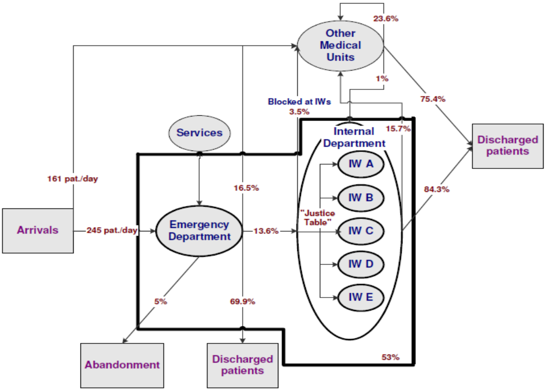
SAMSI Data-Driven Decisions in Healthcare: Opening Workshop

Patient Flow Analysis



Patient Flow Analysis: DATA

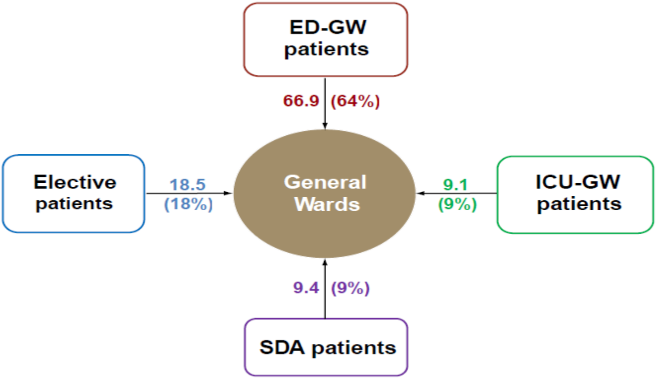
DATA gives the patient flow structure



Resource: Mandelbaum et al. (2011)

Patient Flow Analysis: DATA

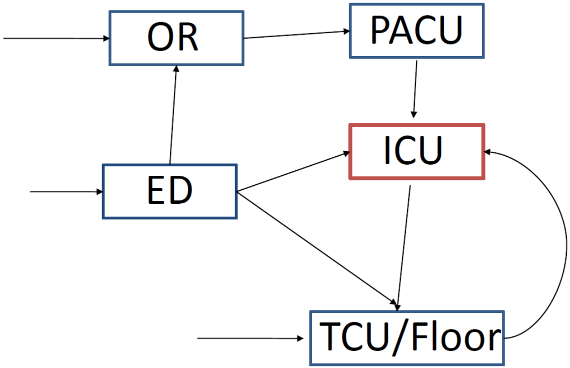
DATA gives the patient flow structure



Resource: Dai et al. (2012)

Patient Flow Analysis: DATA

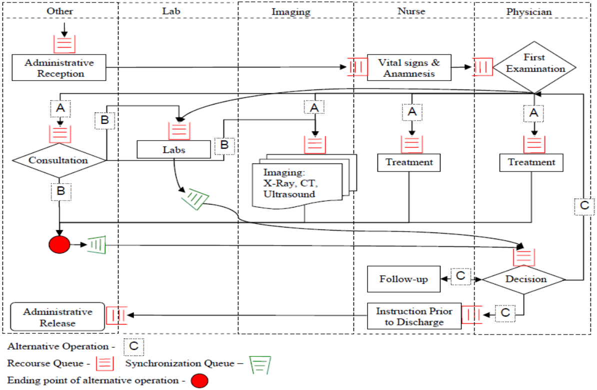
DATA gives the patient flow structure



Resource: Chan et al. (2011)

Patient Flow Analysis: DATA

DATA gives the patient flow structure

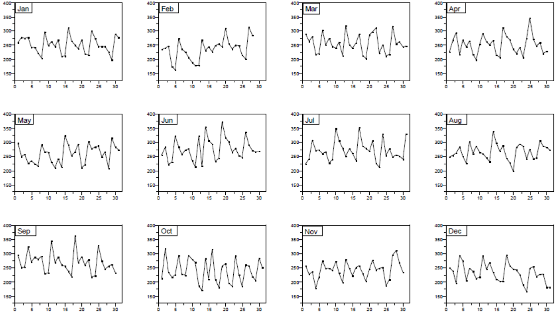


Resource: Mandelbaum et al. (2011)

Patient Flow Analysis: DATA

DATA provides the patient flow characteristics

Daily arrival rate (by month) to Emergency Department

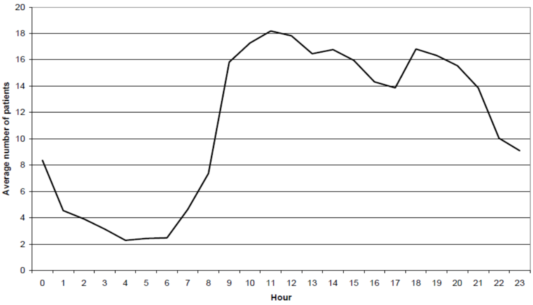


Resource: Yom-Tov (2011)

Patient Flow Analysis: DATA

DATA provides the patient flow characteristics

Hourly arrival rate to Emergency Department

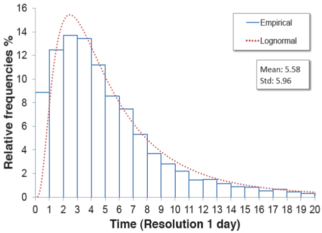


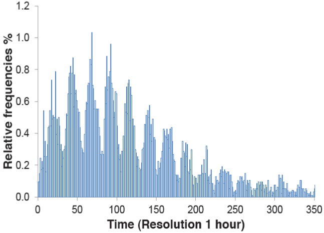
Resource: Yom-Tov (2011)

Patient Flow Analysis: DATA

DATA provides the patient flow characteristics

LOS Distribution of IW

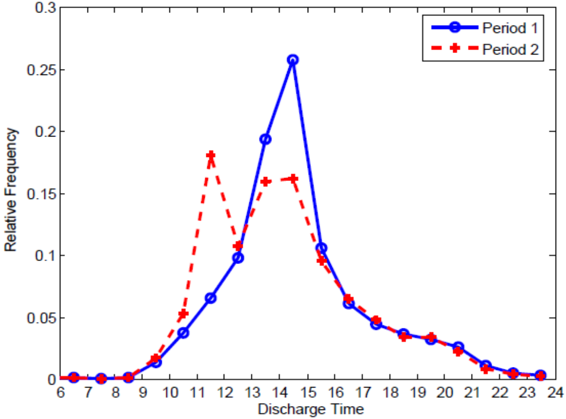




Resource: Mandelbaum et al. (2011)

Patient Flow Analysis: DATA

DATA provides the patient flow characteristics



Resource: Dai et al. (2012)

Patient Flow Analysis: DATA

DATA shows management challenges

- How can the performance measures be stabilized with time-varying arrival patterns?

- How to reduce the ICU congestion while providing good patient outcomes?

- What are the optimal discharge policies to streamline the patient flows more efficiently?

Patient Flow Analysis: MODEL

Patient Flows as Queueing Networks

What is NEW?

- Customers: Patients

- Servers: Beds, Doctors, Nurses, Equipments

- Stations: Medical Units

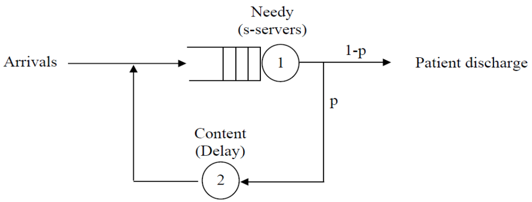
- Service Discipline

- Routing and Control Policies

Patient Flow Analysis: MODEL

Patient Flows as Queueing Networks

Erlang R Model for ED

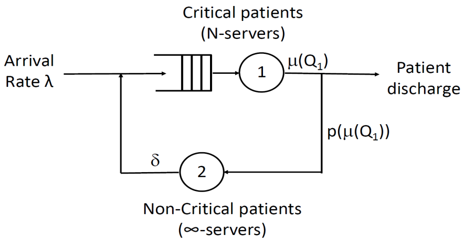


Resource: Mandelbaum and Yom-Tov (2011)

Patient Flow Analysis: MODEL

Patient Flows as Queueing Networks

ICU Model with Speedup

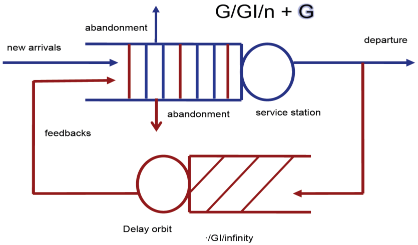


Resource: Chan et al. (2011)

Patient Flow Analysis: MODEL

Patient Flows as Queueing Networks

Impatience Differentiation



Resource: Kang and Pang (2012)

Patient Flow Analysis: MODEL

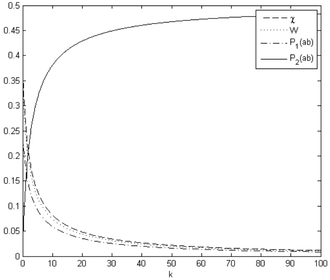
Impatience Differentiation

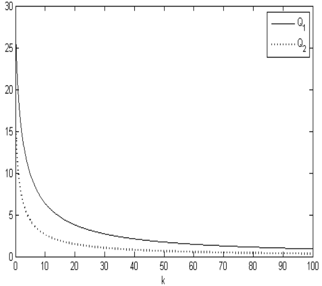
Markovian Models: $\lambda = 60$, $\mu = 1$, $n = 100$, $p = 0.5$, $\delta = 0.5$

Model	$\theta_1 = \theta_2 = 0.5$		$\theta_1 = 0.5$, $\theta_2 = 0.8$		$\theta_1 = 0.8$, $\theta_2 = 0.5$	
	Sim.	Approx.	Sim.	Approx.	Sim.	Approx.
Q_1	11.31	10.90	9.02	9.01	8.55	8.64
Q_2	8.95	9.09	6.98	7.07	6.87	6.95
$P_1(ab)$	0.0897	0.0909	0.0721	0.0723	0.1051	0.1094
$P_2(ab)$	0.0887	0.0909	0.1092	0.1134	0.0671	0.0695
W	0.1791	0.1823	0.1502	0.1468	0.1416	0.1427

Patient Flow Analysis: MODEL

Impatience Differentiation





$G^s \sim H_2(m^s = 1, c_s^2 = 2),\ G^d \sim H_2(0.5, 1.5),\ G_1^r \sim H_2(2, 3),\ G_2^r \sim H_2(2/k, 3),$
$\lambda = 80,\ p = 0.4,\ N = 100$

Patient Flow Analysis: MODEL

Models with Dependent Service Times

$M^B/M^D/n$ queue: Marshall-Olkin multivariate exponential within each batch with correlation ρ, $\mu = 1$, $\lambda_B = 50$, $B \sim Geom(0.5)$, $n = \lambda_B m_B/\mu + \beta\sqrt{\lambda_B m_B/\mu} = 110$, $\beta = 1$. Delay probability $P(W > 0) \approx \alpha(\beta/\sqrt{z})$

where $\alpha(\beta) = (1 + \beta\Phi(\beta)/\phi(\beta))^{-1}$ is the Halfin-Whitt function, and z is the peakedness measure in the associated $G/G/\infty$ queue, equal to the steady state variance divided by mean of the number in system. Here $z \approx 2 + \rho$.

ρ	Sim.	Approx.
0	0.3656	0.3663
0.1	0.3766	0.3764
0.2	0.3857	0.3860
0.3	0.3946	0.3951
0.4	0.4041	0.4039
0.5	0.4126	0.4122

Source: Pang and Whitt (2011)

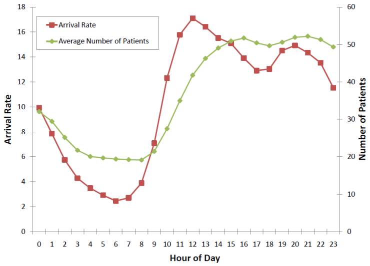
Patient Flow Analysis: MODEL

Models with Time-Varying Arrival Rates

How to compute the time-varying performance measures?

Fluid Models

- Markovian models: ODE
- non-Markovian models: algorithms
  - Liu and Whitt (2011)
  - Kang and Pang (2011)



Source: Mandelbaum et al. (2011)

Patient Flow Analysis: MODEL

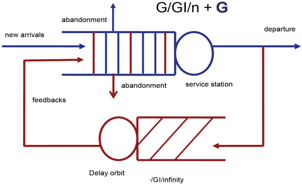
Models with Time-Varying Arrival Rates

How to compute the time-varying performance measures?

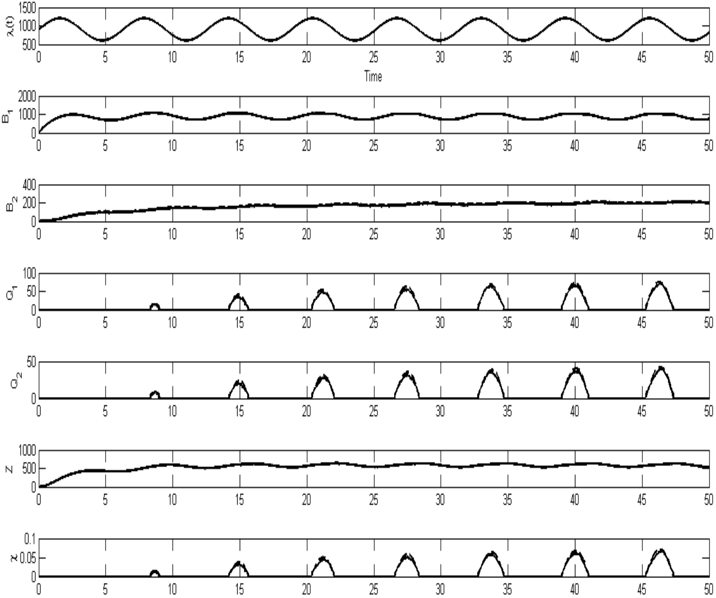
$\lambda(t) = 900 + 300\sin(t),\ N = 1200\ (N = 650)$

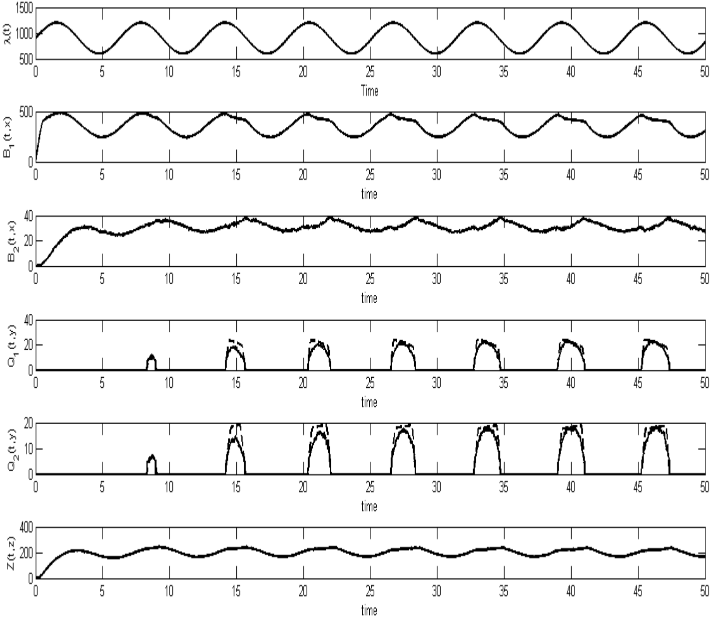
- Service time of new customers $LN(-1/2, 1)$, $m_1^s = 1$
- Service time of reentrant customers $LN(\log(0.5) - 4, 2\sqrt{2})$, $m_2^s = 0.5$
- Patience time of new customers $H_2(1, 3.5)$
- Patience time of reentrant customers $H_2(2, 6)$
- Delay time $H_2(1, 4)$
- Reentrant probability $p = 0.4$

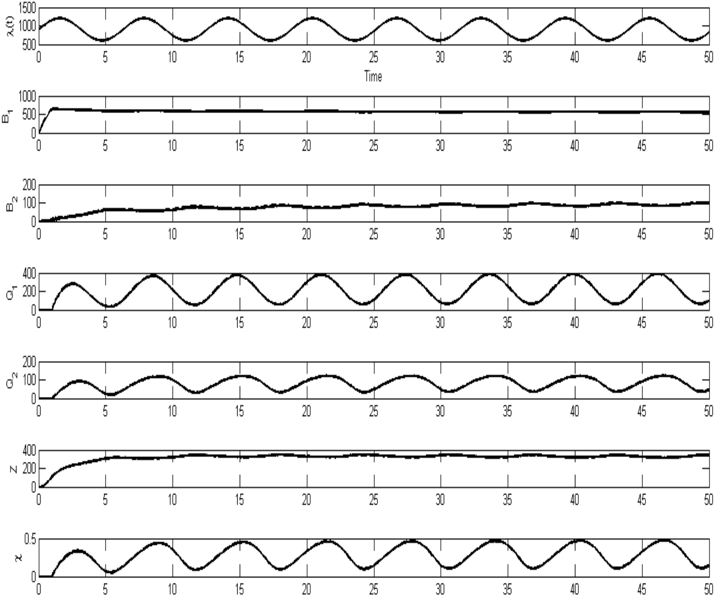
Impatience Differentiation

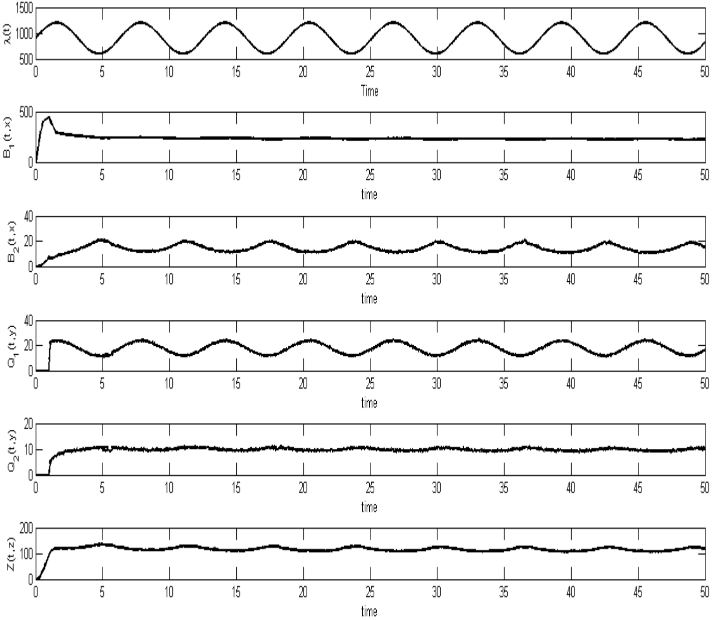


Source: Kang, Lu and Pang (2012)


λ(t)
1500
1000
500
Time
B1
2000
1000
0
B2
400
200
0
Q1
100
50
0
Q2
50
0
Z
1000
500
0
χ
0.1
0.05
0
0 5 10 15 20 25 30 35 40 45 50


1500
1000
500
λ(t)
0
5
10
15
20
25
30
35
40
45
50
Time
500
0
B1(t,x)
time
40
20
0
B2(t,x)
time
40
20
0
Q1(t,y)
time
20
10
0
Q2(t,y)
time
400
200
0
Z(t,z)
time


λ(t)
Time
B1
B2
Q1
Q2
Z
x



λ(t)
Time
B1(t,x)
B2(t,x)
Q1(t,y)
Q2(t,y)
Z(t,z)
time

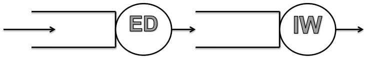
Patient Flow Analysis: MODEL

Many Open Problems

An Integrated System

Challenges:

- ED and IW in different time scales (hours, days)
- Patients receive service while waiting
- Structural dependence



Patient Flow Analysis: Practice

How can we use the models to guide practice?

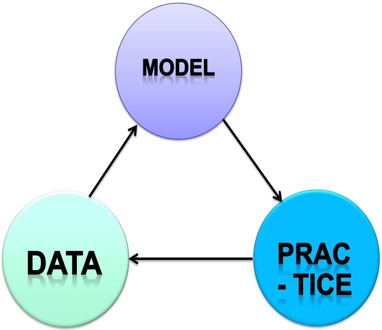
- Stabilizing performance (Liu and Whitt (2011))
- Admission and speedup decisions (Chan et al. (2011))
- Staffing with service dependence (Pang and Whitt (2011))
- Model Validation and Parameter Estimations (Chan et al. (2011))
- Predictions

Patient Flow Analysis: Practice

Model Validation and Parameter Estimations

- **Validate the model assumptions from the data**
- **Estimate the model parameters from the data**
- **Use the model to help with inference**

Patient Flow Analysis



Better FLOW $\Rightarrow$ Better CARE

THANK YOU!