Emergency-Departments Simulation in Support of Service-Engineering: Staffing, Design, and Real-Time Tracking

Yariv N. Marmor

Advisor: Professor Mandelbaum Avishai

Faculty of Industrial Engineering and Management
Technion – Israel Institute of Technology

Original advisor : Late Dr. David Sinreich (02.02.2007)

Motivation - ED overcrowding

- **Staff (re)scheduling** (off-line) using simulation:
  - Sinreich and Jabali (2007) – maintaining **steady utilization**.
  - Badri and Hollingsworth (1993), Beaulieu et al. (2000) – **reducing Average Length of Stay** (ALOS).
- Alternative **operational** ED **designs**:

  King et al. (2006), Liyanage and Gale (1995) – aiming mostly at reducing **ALOS**.
- Raising also the patients' view: **Quality of care**

  Green (2008) – **reducing waiting times** (also the time to first encounter with a physician).

The rest of the presentation

Part 1: Intraday staffing

a. In real-time.

b. Over mid-term.

Part 2: Find an efficient operating model for an operational environment.

Part 3: (if time permits) Long-term benefits of using real-time patients tracking (RFID) in the ED.

Part 1a: Intraday staffing in real-time

Special thanks:

Prof. Shtub, Dr. Wasserkrug, Dr. Zeltyn

Objectives

- [Obtain **real data** in **real-time** regarding current state.]
- **Complete the data** when necessary via simulation.
- **Predict short-term** evolution and workload.
- Proceed with simulation and mathematical models **(Staffing)** as **decision support tools.**

- All the above in real-time or close to real-time

Research framework and basic ED simulation model

- Rambam's ED admits over 80,000 patients per year:
  - 58% classified as **Internal**.
  - 42% classified as **Surgical or Orthopedic**.
- The ED has three major areas:

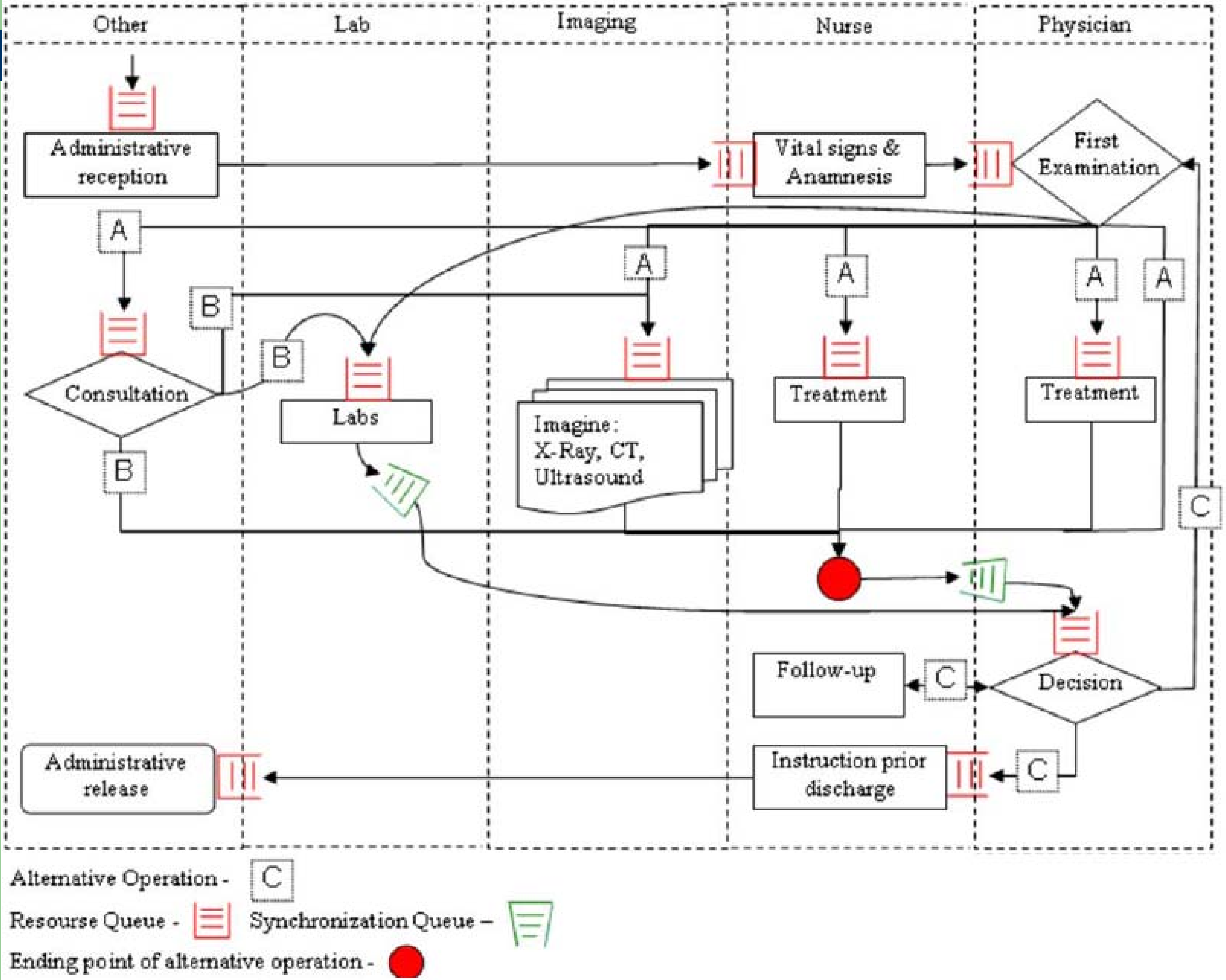
  (1) Internal acute (2) Trauma acute (3) Walking.

Research framework and basic ED simulation model

Research framework and basic ED simulation model

- Generic simulation tool (Sinreich and Marmor ,2005).
- ED resource-process chart:

Research framework and basic ED simulation model



Estimation of current ED state

- **Goal** – Estimate current ED state (using simulating):
  - **Number** of the different types of **patients**.
  - **Patients' state** in the ED process (e.g. X-ray, Lab, etc.)

  [cannot be extracted from most of currently installed IT systems]

- Data available (problem):
  - **Accurate data** - taking actual arrivals into account.
  - **Inaccurate data** - taking discharges into account:
    - Hospitalization (no ward immediately available).
- Method to estimate state at t=0:

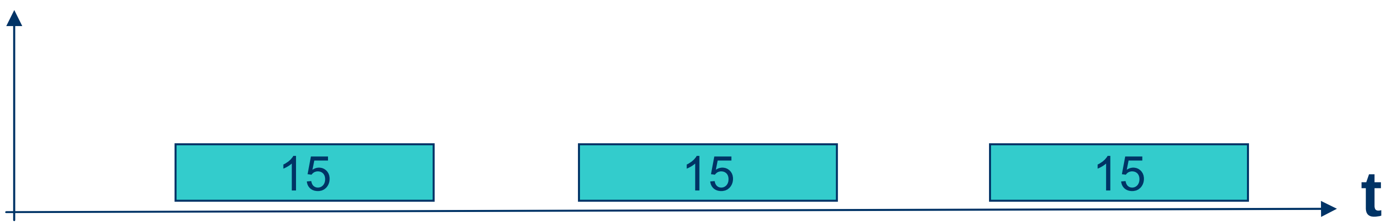
  Run ED simulation from "t=-∞"; keep replications that are consistent with the observed data (# of discharged)

Required staffing level – short-term prediction

Staffing models:

- **RCCP** (Rough Cut Capacity Planning) - Model aims at **operational efficiency** (resource utilization level).

- **OL** (Offered Load) - Model aims at **operational** and **quality of service** (time till first encounter with a physician).



RCCP - Rough Cut Capacity Planning (Vollmann *et al.*, 1993)

$$RCCP_r(t) = \sum_i A_i(t) d_{ir}$$

$RCCP_r(t)$ - total expected time required from each resource r at time t.

r – resource type ; t - forecasted hour ; i – patient type

$A_i(t)$ - average number of external arrivals of patients of type i at hour t.

d_{ir} - average total time required from each resource r for each patient type i.

$$n_r(RCCP, t) = \frac{RCCP_r(t)}{f_s}$$

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

f_s - safety staffing factor, e.g. $f_s=0.9$ (90%).

We expect RCCP to achieve utilization levels near f_s, but to fail in quality of service. This is remedied by our next OL approach

OL – Offered Load (theory)

In the simplest **time-homogeneous** steady - state case:

R - the offered load is:

λ – arrival rate,

E(S) – expected service time,

$$\boxed{R = \lambda * E(S)}$$

The "Square-Root Safety Staffing" rule: (Halfin & Whitt ,1981):

$$\boxed{n \approx R + \beta\sqrt{R}}$$

$\beta > 0$ is a tuning parameter.

This rule gives rise to **Quality and Efficiency-Driven** (**QED**) operational performance, in the sense that it carefully <u>balances</u> **high service quality** with **high utilization levels** of resources.

OL – Offered Load (theory) - time-inhomogeneous

Arrivals can be modeled by a **time-inhomogeneous** Poisson process, with arrival rate $\lambda(t)$; $t \geq 0$:

OL 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):

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

S - a (generic) service time.

OL – Offered Load (theory) - time-inhomogeneous

QED approximation for achieving service goal α:

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

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

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

α - 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),

Offered Load methodology for ED staffing

- ∞ servers: the simulation model is run with "infinitely-many" resources (e.g. physicians, or nurses, or both).
- Offered Load: for each resource *r* (e.g. physician or nurse) and each hour *t*, we calculate the number of busy resources (equals the total work required), and use this value as our estimate for the offered load *R(t)* for resource *r* at time *t*. (The final value of *R(t)* is calculated by averaging over simulation runs).
- Staffing: for each hour *t* we deduce a recommended staffing level $n_r(OL,t)$ via the formula:

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

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

Methodology for short-term forecasting and staffing

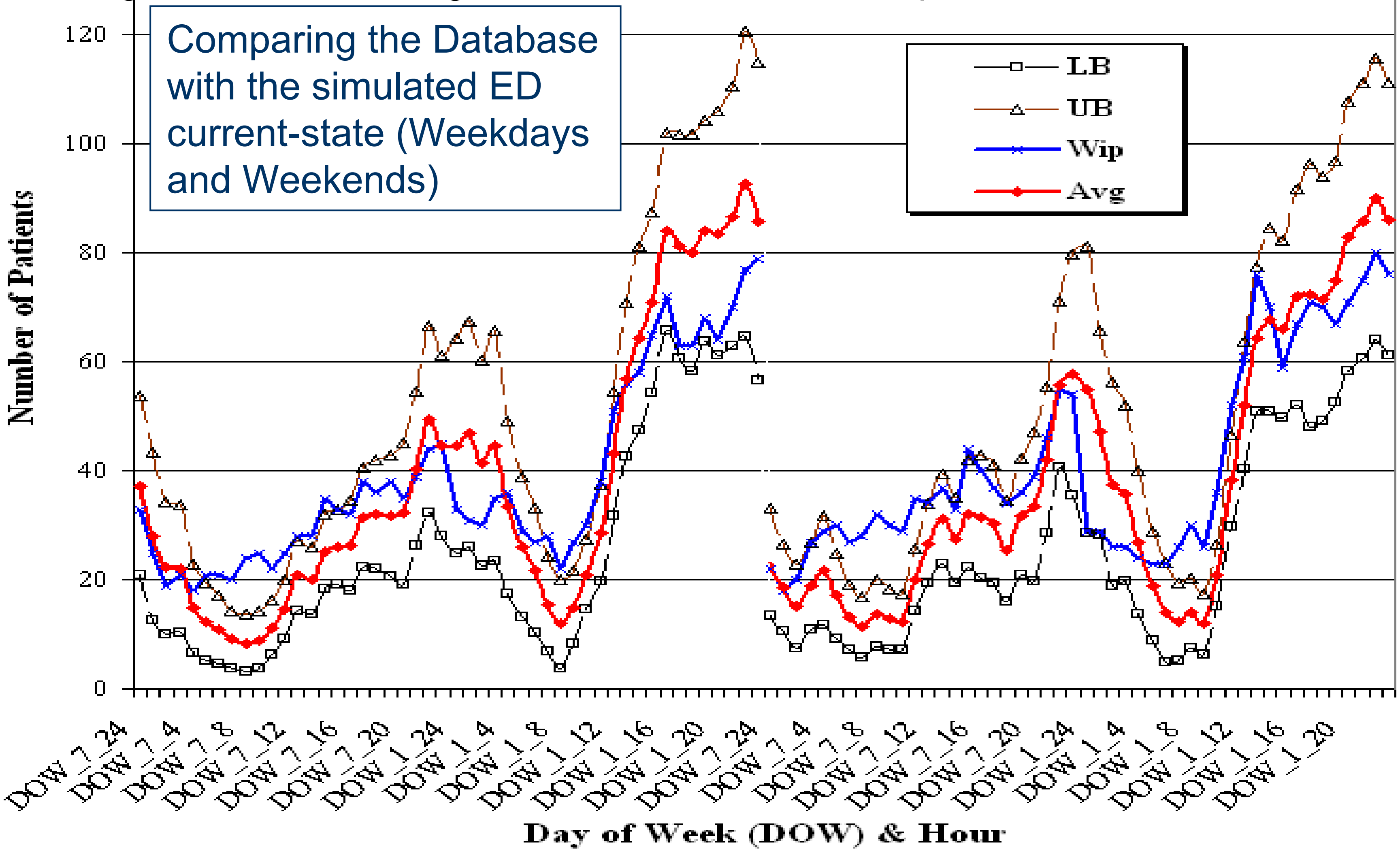
Our simulation-based methodology for short-term staffing levels, over 8 future hours :

1) Initialize the simulation with the **current ED state**.
2) Use the average arrival rate, to generate **stochastic arrivals** in the simulation.
3) Simulate and collect data every hour, over 8 future hours, using **infinite resources** (nurses, physicians).
4) From Step 3, calculate **staffing** recommendations, both $n_r(RCCP,t)$ and $n_r(OL,t)$.
5) Run the **simulation** from the current ED state with the **recommended staffing** (and existing staffing).
6) Calculate **performance** measures.

Simulation experiments – current state (# patients)

n=100 replications, Avg-simulation average, SD-simulation standard deviation, UB=Avg+1.96*SD, LB=Avg-1.96*SD, WIP-number of patients from the database

Comparing the Database with the simulated ED current-state (Weekdays and Weekends)



Simulation experiments – current state (index)

Simulation performance measures - current 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 α).

	Utilization						
Hour	Ip	Sp	Op	Nu	#Beds	#Chairs	%W
09-10	73%	1%	23%	55%	15.7	8.6	7%
10-11	93%	25%	59%	68%	23.5	17	33%
11-12	94%	59%	67%	72%	29.3	22.8	51%
12-13	90%	45%	81%	58%	33.2	30.3	53%
13-14	95%	68%	94%	71%	36.2	34.7	77%
14-15	90%	62%	76%	63%	34.2	33.3	70%
15-16	91%	51%	46%	51%	34.4	30.5	77%
16-17	100%	43%	41%	53%	34.6	27.6	69%
17-18	95%	58%	46%	57%	33.4	23.6	52%
18-19	90%	46%	52%	50%	32.4	23.9	31%
19-20	89%	64%	70%	58%	29.3	25.3	40%
20-21	79%	64%	75%	56%	26.5	20.6	39%
21-22	84%	46%	60%	45%	23.4	17	23%
22-23	66%	38%	51%	46%	20.2	13.9	20%

Simulation experiments – staffing recommendation

Staffing levels (present and recommended)

	n (Current)				Offered Load				n (OL)				RCCP Load				n (RCCP)			
Hour	I_p	S_p	O_p	N_u	I_p	S_p	O_p	N_u	I_p	S_p	O_p	N_u	I_p	S_p	O_p	N_u	I_p	S_p	O_p	N_u
16-17	4	1	2	5	7.8	0.8	0.8	4.1	9	2	2	5	3	0.5	0.6	2.4	4	1	1	3
17-18	4	1	2	5	3.7	0.4	0.9	2.5	5	1	2	3	3.3	0.4	0.7	1.3	4	1	1	2
18-19	4	1	2	5	3.2	0.4	1.1	2.7	4	1	2	4	2.3	0.4	0.4	1.3	3	1	1	2
19-20	4	1	2	5	2.3	0.5	1.2	2.5	3	1	2	3	2.4	0.5	0.6	1	3	1	1	2
20-21	4	1	2	5	2.7	0.6	1.5	2.7	4	1	2	4	2.3	0.5	0.4	1	3	1	1	2
21-22	4	1	2	5	2.4	0.4	1.3	2.4	3	1	2	3	2.8	0.5	0.4	1.1	4	1	1	2
22-23	4	1	2	5	2.3	0.2	0.9	2	3	1	2	3	2.4	0.3	0.2	1	3	1	1	2

Simulation experiments – comparisons

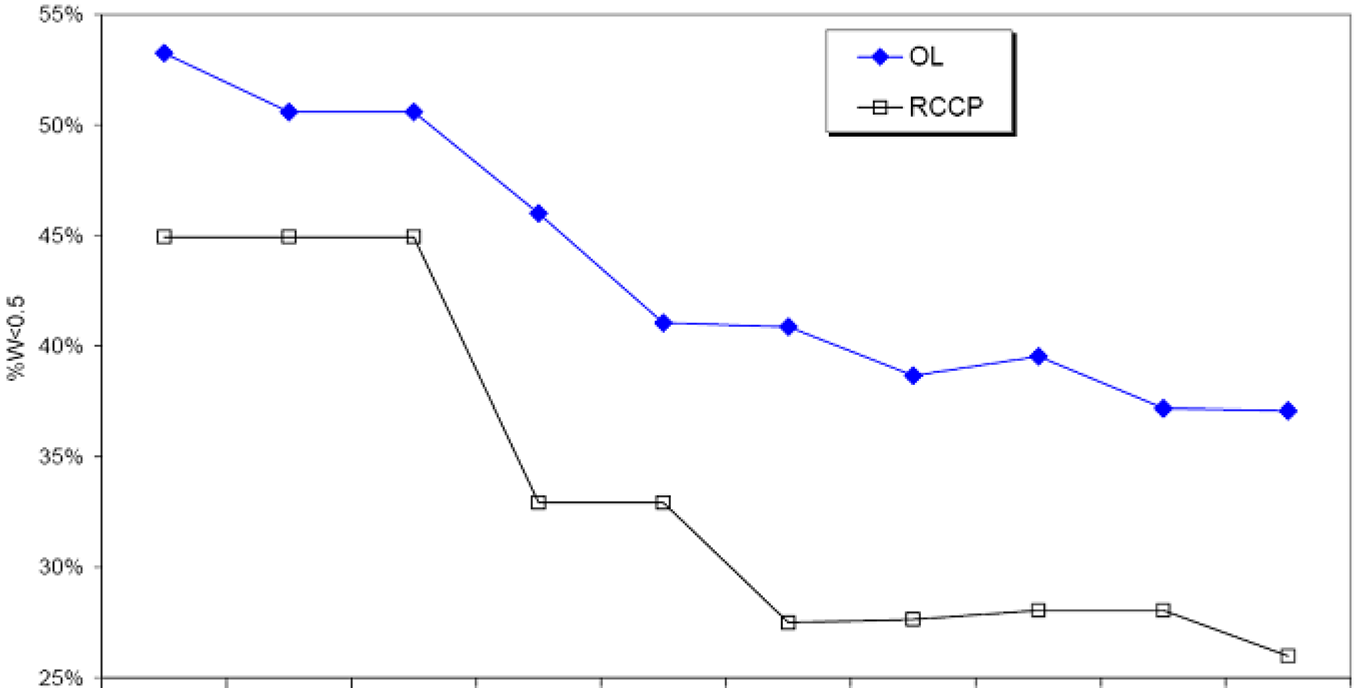
	Performance measures using OL recommendation							Performance measures using RCCP recommendation						
	Resource Utilization				#Beds	#Chair	%W	Resource Utilization				#Beds	#Chair	%W
Hour	Ip	Sp	Op	Nu				Ip	Sp	Op	Nu			
16-17	62%	38%	40%	58%	36	29	**56%**	90%	54%	60%	59%	38.3	35.3	**78%**
17-18	59%	33%	35%	67%	34.8	31.6	**36%**	82%	47%	65%	81%	39.3	40.2	**82%**
18-19	75%	49%	53%	76%	32.2	29.9	**46%**	80%	45%	69%	92%	40.6	46.2	**86%**
19-20	84%	48%	57%	80%	31.5	31.1	**38%**	72%	43%	79%	97%	42.3	52.2	**90%**
20-21	76%	52%	65%	71%	28.7	28.4	**38%**	68%	46%	85%	99%	43.4	57.7	**91%**
21-22	83%	49%	59%	75%	27.8	27.9	**42%**	55%	45%	89%	99%	44.7	62.4	**91%**
22-23	85%	45%	50%	73%	25.7	25.4	**50%**	63%	39%	87%	99%	45.9	64.9	**91%**

OL method achieved good service quality: *%W* is stable over time.

RCCP method yields good performance of resource utilization - near 90%.

Simulation experiments – comparisons

Comparing RCCP and OL given the same average number of resources



*	3.00	3.00	3.00	2.71	2.71	2.64	2.61	2.54	2.54	2.32
**	3.00	2.93	2.86	2.79	2.68	2.64	2.57	2.54	2.46	2.43
***	5%	9%	11%	14%	32%	34%	39%	51%	66%	90%

* avg number of resources per hour (RCCP)
** avg number of resources per hour (OL)
*** α

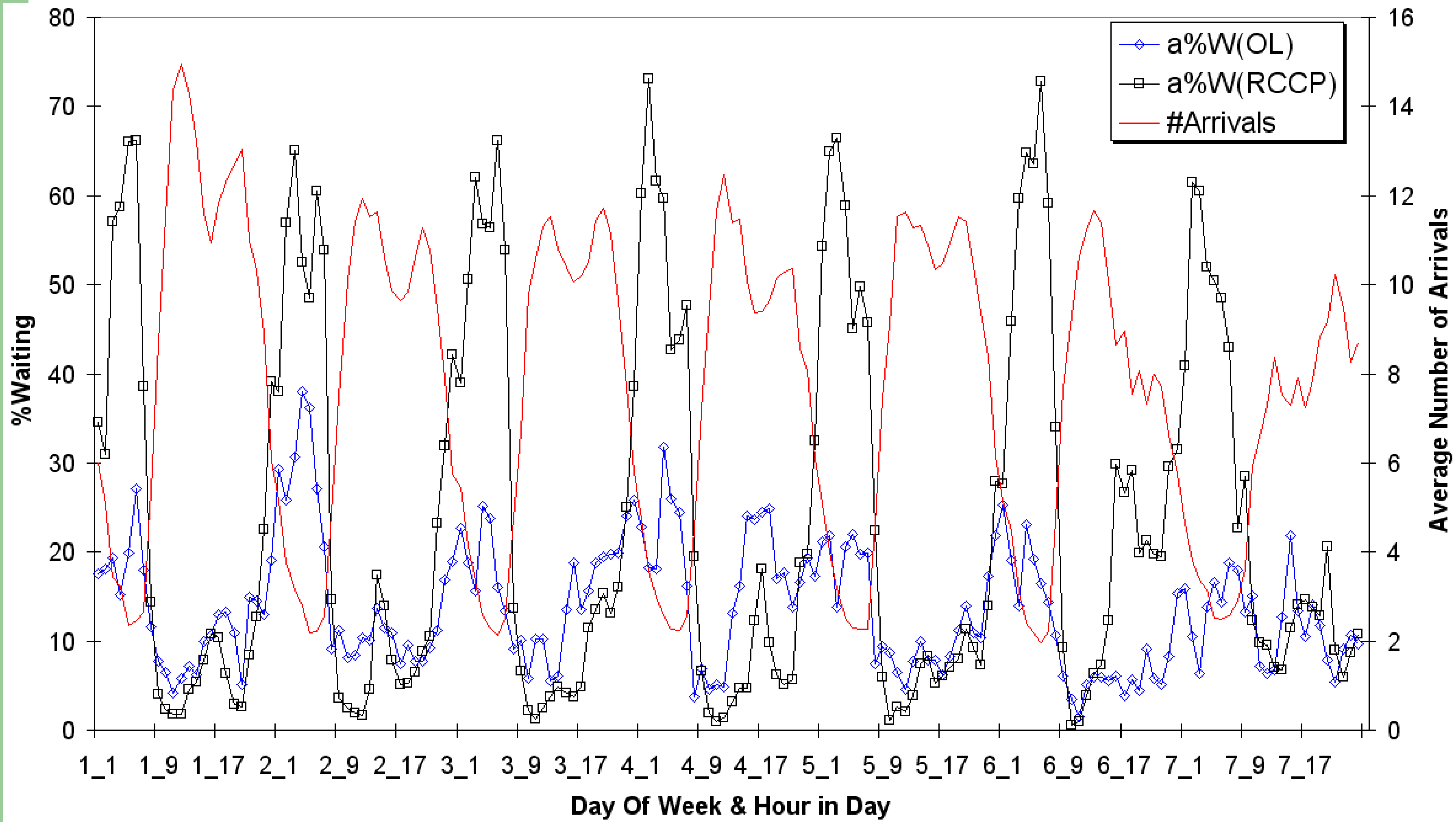
The simulation results are conclusive – OL is superior, implying higher quality of service, with the same number of resources, for all values of α.

Part 1b: Intraday staffing over the mid-term

Special thanks: Dr. S. Zeltyn

Mid-term staffing: Results

%W (and #Arrivals) per Hour by Method in an Average Week (α = 0.3)



Conclusions and future research

- We develop a staffing methodology for achieving both high utilization and high service level, over both short- and mid-term horizons, in a highly complex environment.
- More work needed:
  - Refining the analytical methodology (now the α is close to target around α = 50%).
  - Introducing constrains into our staffing methodology.
  - Incorporate more detailed data (e.g. from RFID).

Part 2: Fitting an efficient operational model to a given ED environment

Special thanks: Prof. B. Golany

Research problem:
matching design to environment (long rang)

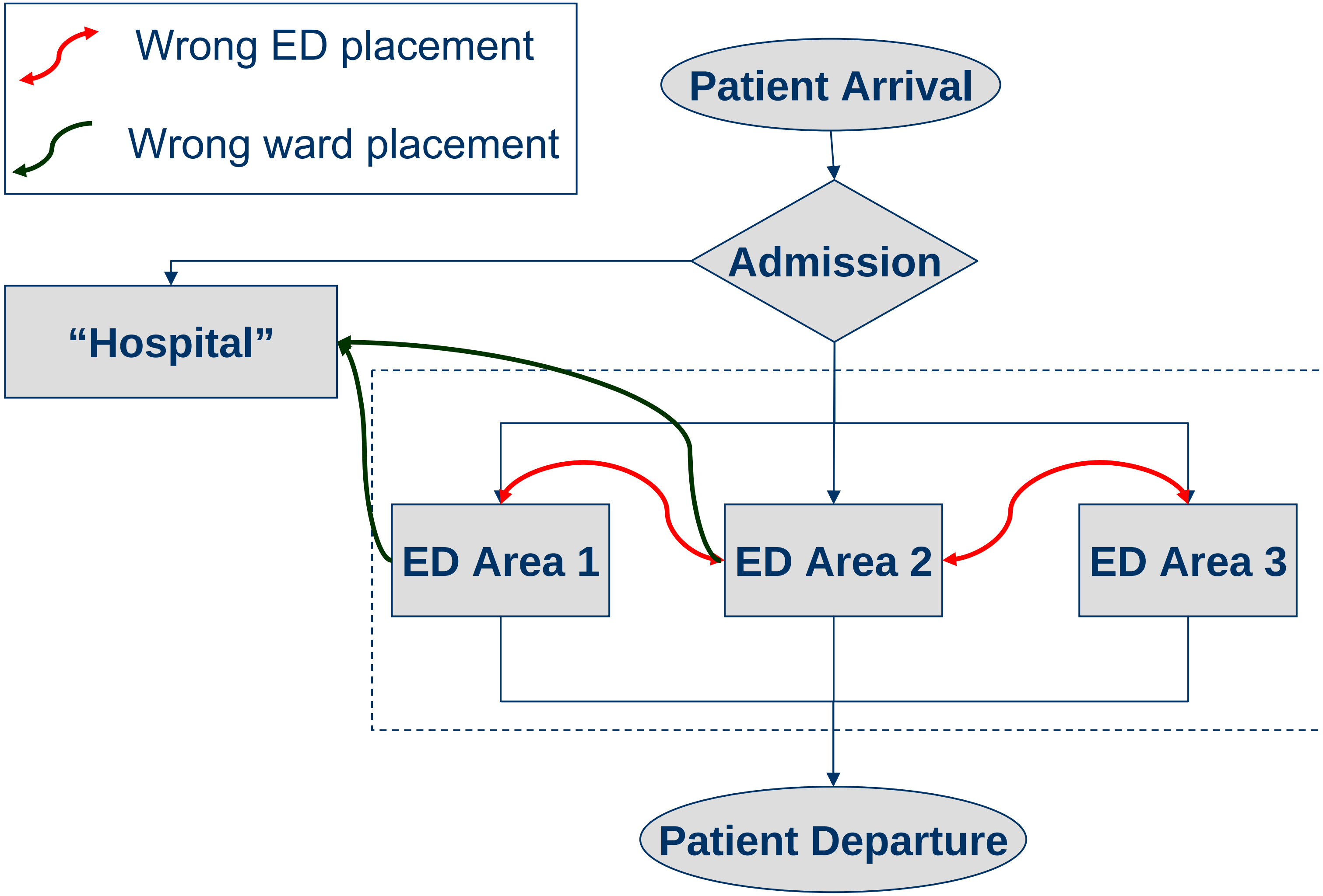
Current practice: Priority queues at the ED are based on patients' urgency and illness type (e.g. Garcia *et al.*, 1995).

Problem: No account of operational considerations, e.g. relieving over crowding by accelerating discharges (SPT).

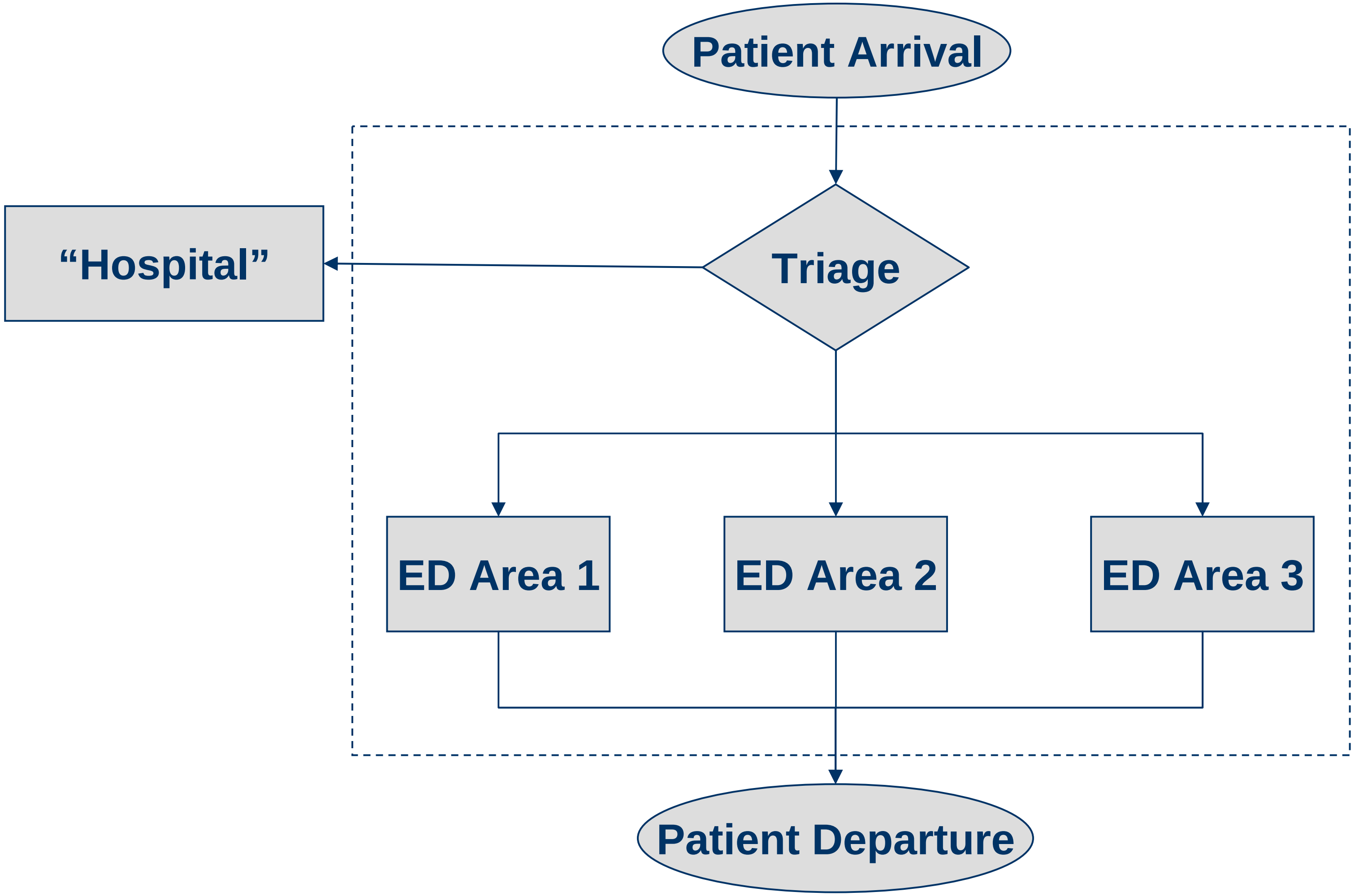
Managerial solution: To use ED structure in order to enforce operational considerations:

- Illness-based (ISO)
- Triage
- Fast Track (FT)
- Walking-Acute (AC)

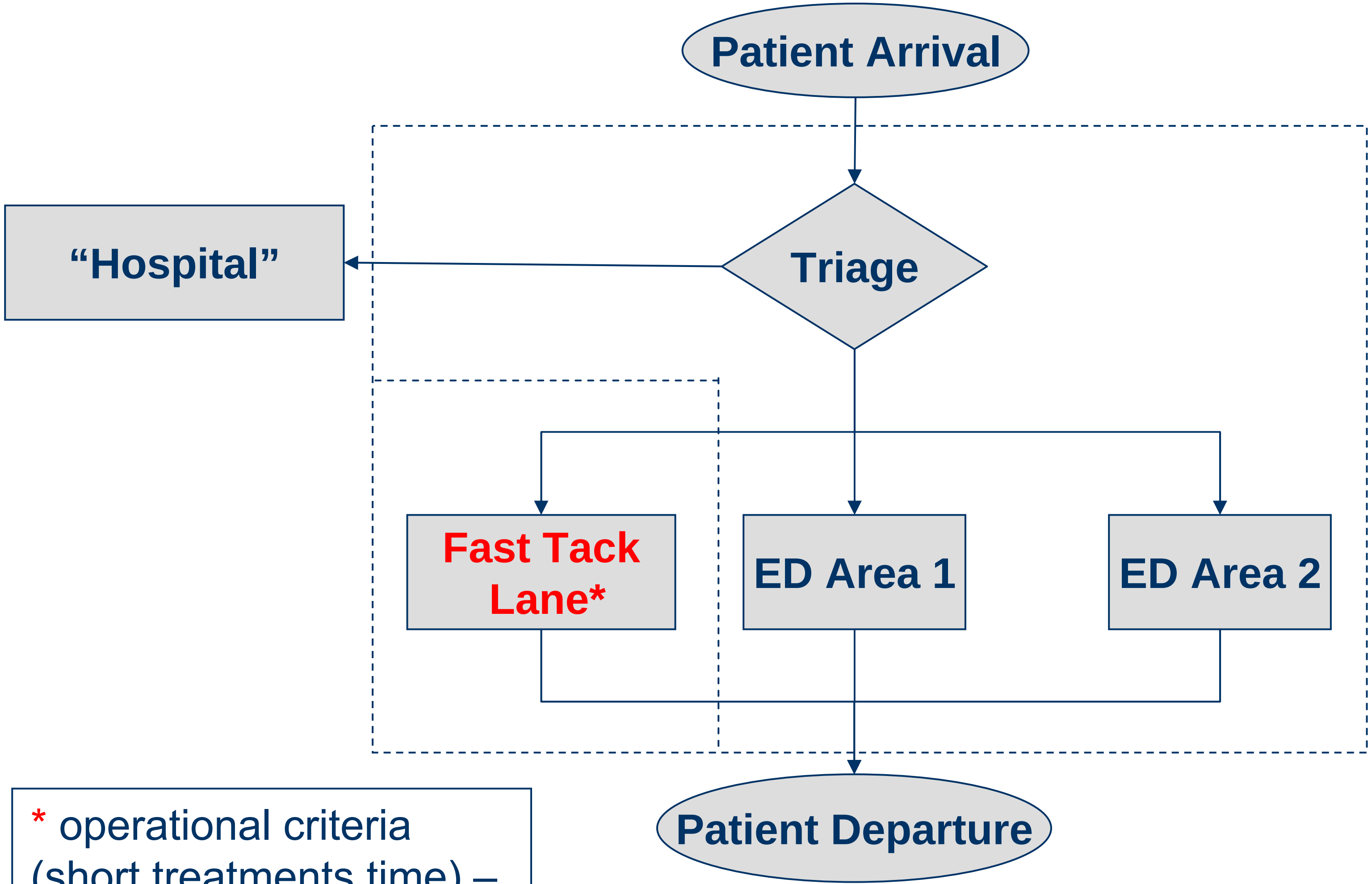
ED design - Illness-based (ISO)



ED design - Triage

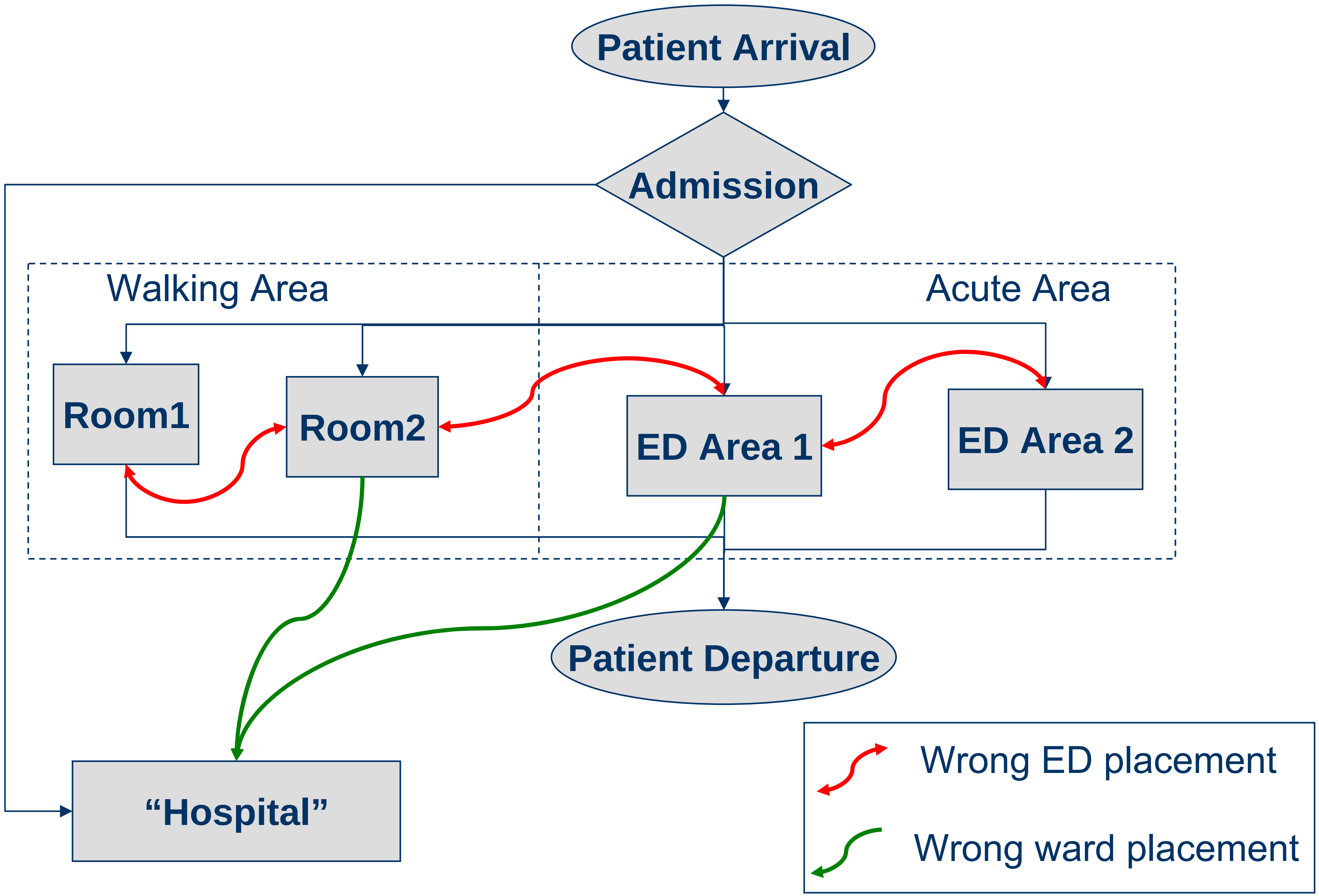


ED design– Fast Track (FT)



* operational criteria (short treatments time) – acute or walking patient

ED design – Walking Acute (WA)



Data Envelopment Analysis (DEA)

- **DEA** is a mathematical technique for evaluating relative performance (efficiency).
- **CCR** is the basic model (by Charnes *et al.* ,1978) that calculates relative efficiencies of complex systems with heterogeneous inputs and outputs.
- **Decision Making Units** (DMU's): compared systems / subsystems (e.g. Hospital X working in operating model Y at month Z).

Data Envelopment Analysis (DEA)

- Including uncontrolled inputs (Banker and Morey, 1986), **Equation ***:

Outputs

Uncontrollable inputs

$$\max \quad \theta_0 = \frac{\sum_{j=1}^{s} w_j y_{j0} - \sum_{k=1}^{t} u_k z_{k0}}{\sum_{i=1}^{r} v_i x_{io}}$$

Controllable inputs

Efficiency

$$\text{s.t.} \quad 1 \geq \frac{\sum_{j=1}^{s} w_j y_{jm} - \sum_{k=1}^{t} u_k z_{km}}{\sum_{i=1}^{r} v_i x_{im}}, \quad m = 1, \ldots n$$

$$w_j > 0, \quad j = 1, \ldots s \quad \text{(weights for outputs)}$$

$$v_i > 0, \quad i = 1, \ldots r \quad \text{(weights for controllable inputs)}$$

$$u_k > 0, \quad k = 1, \ldots t \quad \text{(weights for uncontrollable inputs)}$$

Objectives and structure

- Goal: Identify the “best” (most efficient) ED operating strategy, via simulation and based on real data, to match an operational model with a given operational environment.
- Contents:
  - ED Design (EDD) methodology
  - Available Data
  - Parameters
  - Results

The EDD (ED Design) methodology

1. Prepare model data (Golany and Roll, 1989) :
   - Select DMUs to be compared.
   - List relevant efficient measurements, operational elements, and uncontrollable elements influencing ED performance.
   - Choose the measurements and elements that would enter the DEA model by:
     - Judgmental approach (I).
     - Statistical (correlation) approach (II).
2. Evaluate the model:
   - Compare the methods (Brockett and Golany,1996).
   - Identify the uncontrollable elements (Environment) that determine the operating methods to reach an efficient system.

Comparing different "programs" using DEA

- Identifying a preferred policy from available options (originally for 2, in Brockett and Golany, 1996) :

I. Split the group of all DMUs ($j = 1, ..., n$) into k programs consisting of $n_1, ..., n_k$ DMUs ($n_1 + n_2 + ... + n_k = n$). Run DEA separately (e.g. Equation *).

II. In each of the k groups separately, adjust inefficient DMUs to their "level at efficiency" value by projecting each DMU onto the efficiency frontier of its group (e.g. by changing the controllable inputs at Equation *).

III. Run a pooled (or "inter-enveloped") DEA with all the n DMUs at their adjusted efficient level (again like in Equation *).

IV. Apply a statistical test to the results of III to determine if the k groups have the same distribution of efficiency values within the pooled DEA set (or is it varies according to different uncontrollable parameters).

Available Data

Hospital	Start Date [Month-Year]	End Date [Month-Year]	Operating Model	Average Monthly Patient Arrivals	ED Scale
1	Apr-1999	Nov-2000	Fast-Track	5700	Medium
2	Apr-1999	Sep-2001	ISO	4200	Small
3	Apr-1999	Jun-2003	Fast-Track	6400	Medium
4	Jan-2000	Dec-2002	WA	6100	Medium
5	Jan-2004	Oct-2007	WA	7600	Large
6	Mar-2004	Feb-2005	Fast-Track	3200	Small
7	Apr-1999	Sep-2001	Triage	3400	Small
8	Aug-2003	Mar-2005	Triage	5500	Medium

Enriching data via simulation

		Ratio for each unrepresented magnitude			Represented Operating model			
Hospital	Month Arrivals	3000 – 5000	5000 – 7000	7000+	FT	Triage	WA	ISO
1	5700	0.64	*	1.34	*			
2	4200	*	1.45	1.81				*
3	6400	0.57	*	1.19	*			
4	6100	0.6	*	1.25			*	
5	7600	0.48	0.8	*			*	
6	3200	*	–	–	*			
7	3400	*	1.79	2.24		*		
8	5500	0.66	*	1.39		*		
Average		3600	6066.67	7600				

Choosing parameters (output)

- **Countable1W**: Number of patients who exit the ED (excluding abandoning, deaths, ED returns after less than **one week**) (2,699-7,576 ; 5,091).
- **Countable2W**: Same as Countable1W but with two weeks (2,586-7,306 ; 4,906).
- **Q_LOS_Less6Hours**: Total number of patients whose length of stay is reasonable (2,684-8,579 ; 5,580).
- **Q_ALOS_P_Minus1**: Average length of stay (ALOS), to the power of -1, multiplied by the average number of hours in a month (119-445 ; 276).
- **Q_notOverCrowded**: Total number of patients who arrived to the ED when the ED was not overcrowded (more patients than beds and chairs) (2,388-8,368 ; 5,290).

Choosing parameters (Controllable inputs)

- **Beds:** Number of bed-hours available per month (840-2,573 ; 1669).
- **WorkForce**: Number of “cost-hours" per month (physician’s hour costs 2.5 times nurse’s hour) (10,900-35,914 ; 18,447).
- **PatientsIn**: Total number of patient arrivals to the ED per month (2,976-8,579 ; 5,717).
- **Hospitalized**: Total number of patients hospitalized after being admitted to the ED per month (541-2,709 ; 1,496).
- **Imaging**: Total “imaging-costs” ordered for ED patients per month (1,312-14,860; 2,709).

Choosing parameters (Uncontrollable inputs)

Age:

- **Child**: Number of patients under the age of 18, arriving to the ED during a month (95-1,742 ; 611).
- **Adult**: Ages 18-55 (1,429-5,728 ; 3,178).
- **Elderly**: Ages over 55 (728-3,598 ; 1,914).

Admission reason:

- **Illness**: Number of patients with admission reason related to illness, arriving to the ED during a month (1,853-6,153 ; 3,775).
- **Injury**: Reason related to injury (779-3,438 ; 1,849).
- **Pregnancy**: Reason related to pregnancy (0-16 ; 3).

Choosing parameters (Uncontrollable inputs) con.

Arrivals mode:

- **Ambulance** (157-1,887 ; 795).
- **WithoutAmbulance** (2,679-7,416 ; 4,921).

Additional information:

- **WithLetter** (1,624-6,536 ; 3,741).
- **WithoutLetter** (803-3,651 ; 1,976).
- **OnTheirOwn** (786-3,579 ; 1,952).
- **notOnTheirOwn** (1,744 - 6,576 ; 3,765).

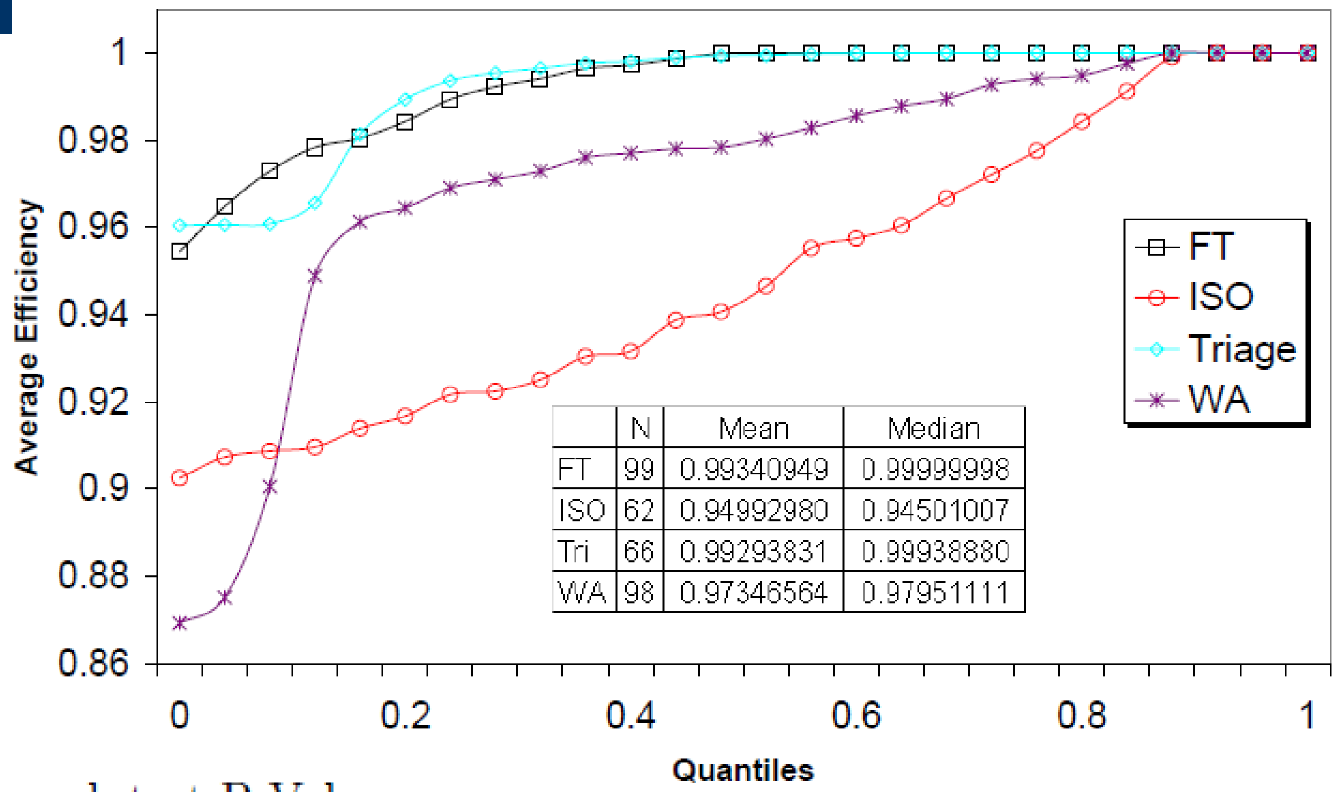
Type of treatment:

- **Int** (1,431 - 5,176 ; 3,062).
- **Trauma** (378 - 4,490 ; 2,655).

Choosing participating parameters via correlation

	Beds	WorkForce	PatientsIn	Hospitalized	Imaging	Child	Adult	Elderly	Illness	Injury	Pregnancy	Ambulance	WithoutAmbulance	WithoutLetter	WithLetter	OnHisOwn	notOnHisOwn	Int	Trauma	Countable1W	Countable2W	Q_LOS_Less6Hours	Q_notOverCrowded
Beds	1																						
WorkForce	0.73	1																					
PatientsIn	0.95	0.78	1																				
Hospitalized	0.8	0.63	0.78	1																			
Imaging	0.82	0.64	0.88	0.7	1																		
Child	0.56	0.26	0.57	0.14	0.4	1																	
Adult	0.89	0.67	0.95	0.78	0.88	0.52	1																
Elderly	0.59	0.73	0.61	0.6	0.52	−0.02	0.39	1															
Illness	0.85	0.78	0.89	0.74	0.73	0.37	0.78	0.75	1														
Injury	0.84	0.58	0.87	0.53	0.69	0.85	0.85	0.25	0.71	1													
Pregnancy	−0.04	0.11	−0.04	0.21	−0.05	−0.34	−0.13	0.35	0.11	−0.29	1												
Ambulance	0.62	0.5	0.69	0.68	0.61	0.28	0.65	0.51	0.65	0.52	0.31	1											
WithoutAmbulance	0.94	0.77	0.98	0.74	0.87	0.59	0.93	0.58	0.87	0.87	−0.12	0.55	1										
WithoutLetter	0.74	0.65	0.74	0.7	0.69	0.28	0.72	0.5	0.7	0.59	−0.03	0.24	0.8	1									
WithLetter	0.88	0.7	0.94	0.68	0.81	0.61	0.88	0.56	0.82	0.84	−0.04	0.78	0.9	0.48	1								
OnHisOwn	0.78	0.62	0.78	0.75	0.74	0.3	0.81	0.44	0.72	0.63	−0.02	0.33	0.82	0.97	0.55	1							
notOnHisOwn	0.86	0.72	0.94	0.66	0.8	0.62	0.85	0.6	0.82	0.84	−0.05	0.77	0.89	0.47	0.99	0.51	1						
Int	0.9	0.75	0.93	0.86	0.88	0.32	0.93	0.59	0.85	0.7	0.02	0.59	0.93	0.82	0.81	0.87	0.79	1					
Trauma	0.84	0.68	0.91	0.57	0.74	0.75	0.81	0.53	0.78	0.9	−0.1	0.68	0.89	0.54	0.93	0.56	0.94	0.7	1				
Countable1W	0.95	0.79	0.99	0.77	0.86	0.61	0.92	0.63	0.89	0.88	−0.05	0.68	0.98	0.75	0.93	0.78	0.93	0.91	0.93	1			
Countable2W	0.95	0.79	0.99	0.77	0.86	0.61	0.93	0.62	0.89	0.88	−0.04	0.68	0.98	0.75	0.93	0.78	0.93	0.91	0.92	1.0	1		
Q_LOS_Less6Hours	0.93	0.72	0.98	0.78	0.87	0.55	0.94	0.58	0.86	0.85	−0.01	0.74	0.95	0.66	0.96	0.72	0.95	0.91	0.9	0.97	0.97	1	
Q_notOverCrowded	0.82	0.68	0.82	0.6	0.66	0.68	0.73	0.49	0.65	0.82	−0.09	0.56	0.81	0.59	0.79	0.58	0.81	0.68	0.85	0.85	0.85	0.79	1
Q_ALOS_P_Minus1	0.19	0.05	0.16	−0.01	−0.03	0.56	0.18	−0.25	0.02	0.46	−0.27	0.28	0.12	−0.14	0.29	−0.14	0.31	−0.05	0.37	0.2	0.2	0.21	0.4

Results – comparing ED designs

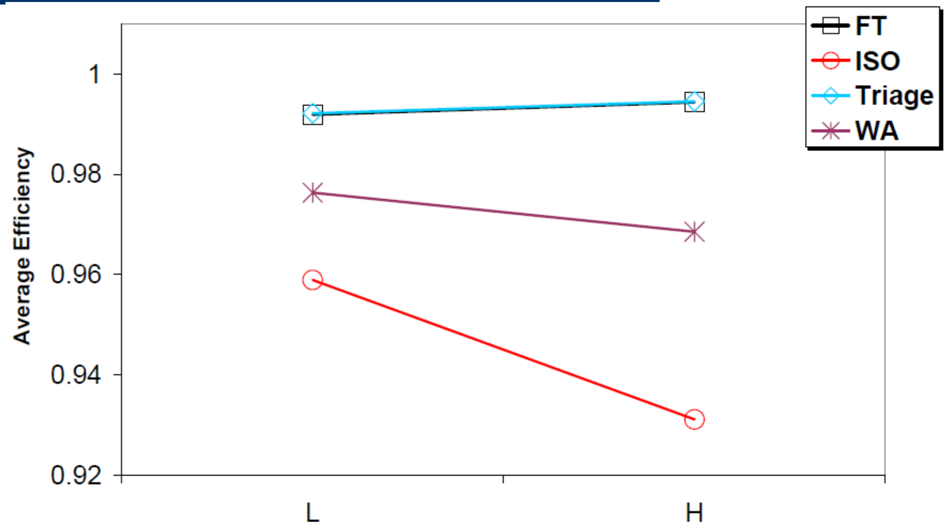


Mann-Whitney rank test P-Value

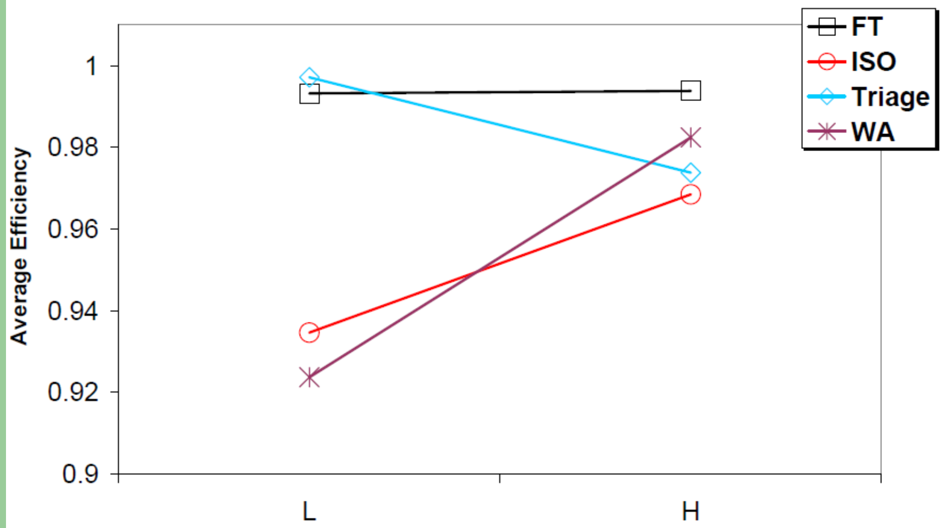
	FT	ISO	Triage
ISO	< .0001	-	-
Triage	0.506	< .0001	-
WA	< .0001	< .0001	< .0001

Conclusion: no dominant design across all data

Identifying models that are more efficient in a given operational environment (interactions)

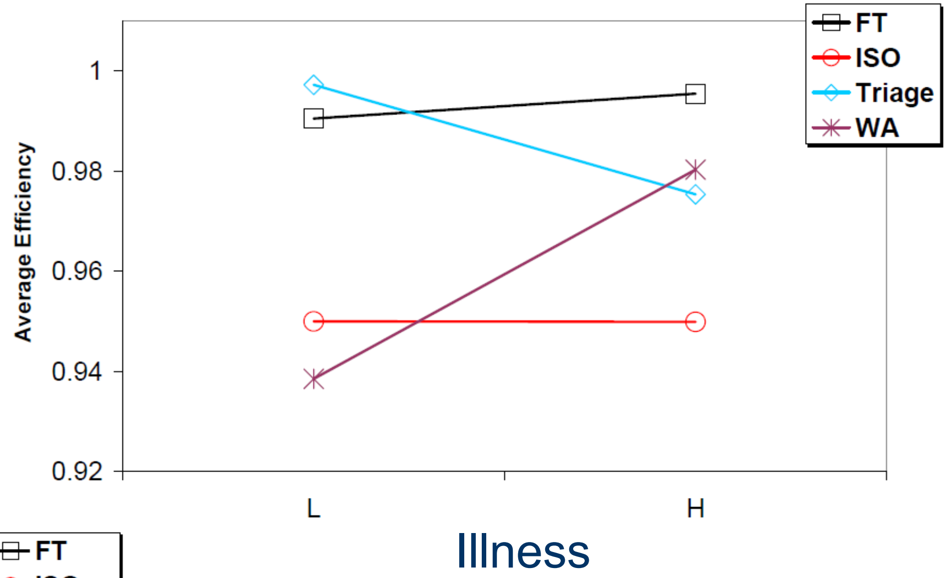


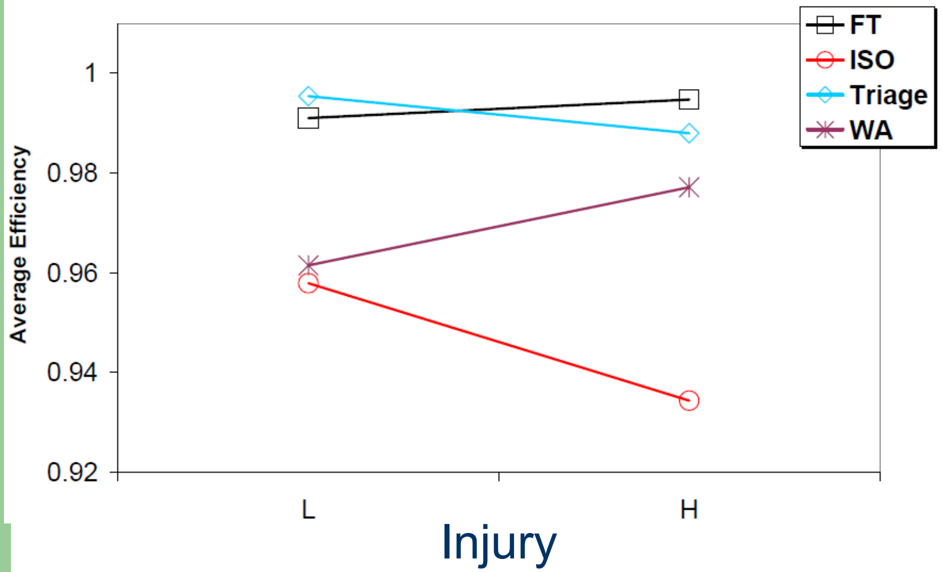
Child



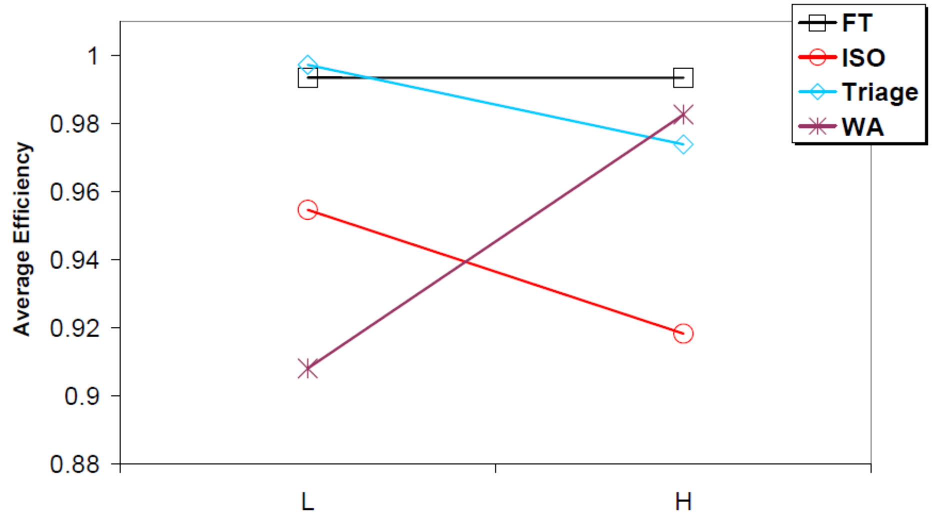
Elderly

Identifying models that are more efficient in a given operational environment (interactions)

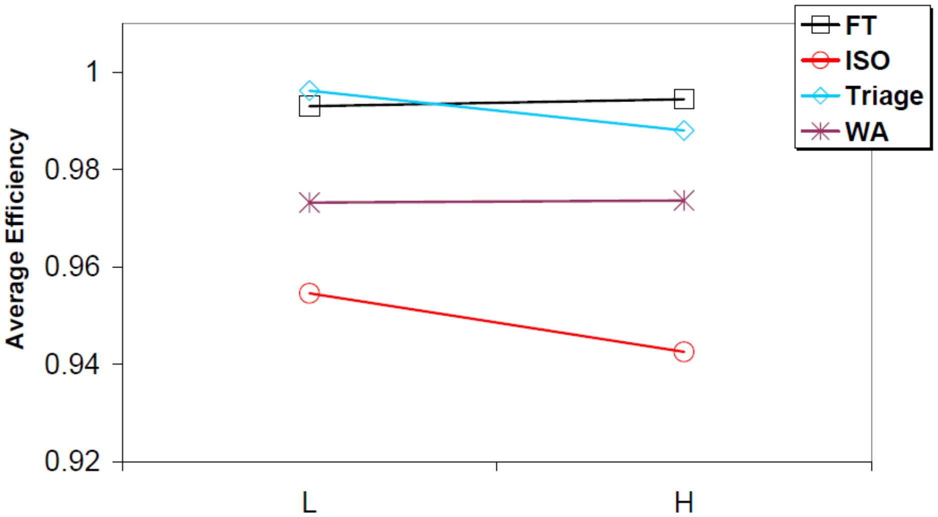




Identifying models that are more efficient in a given operational environment (interactions)



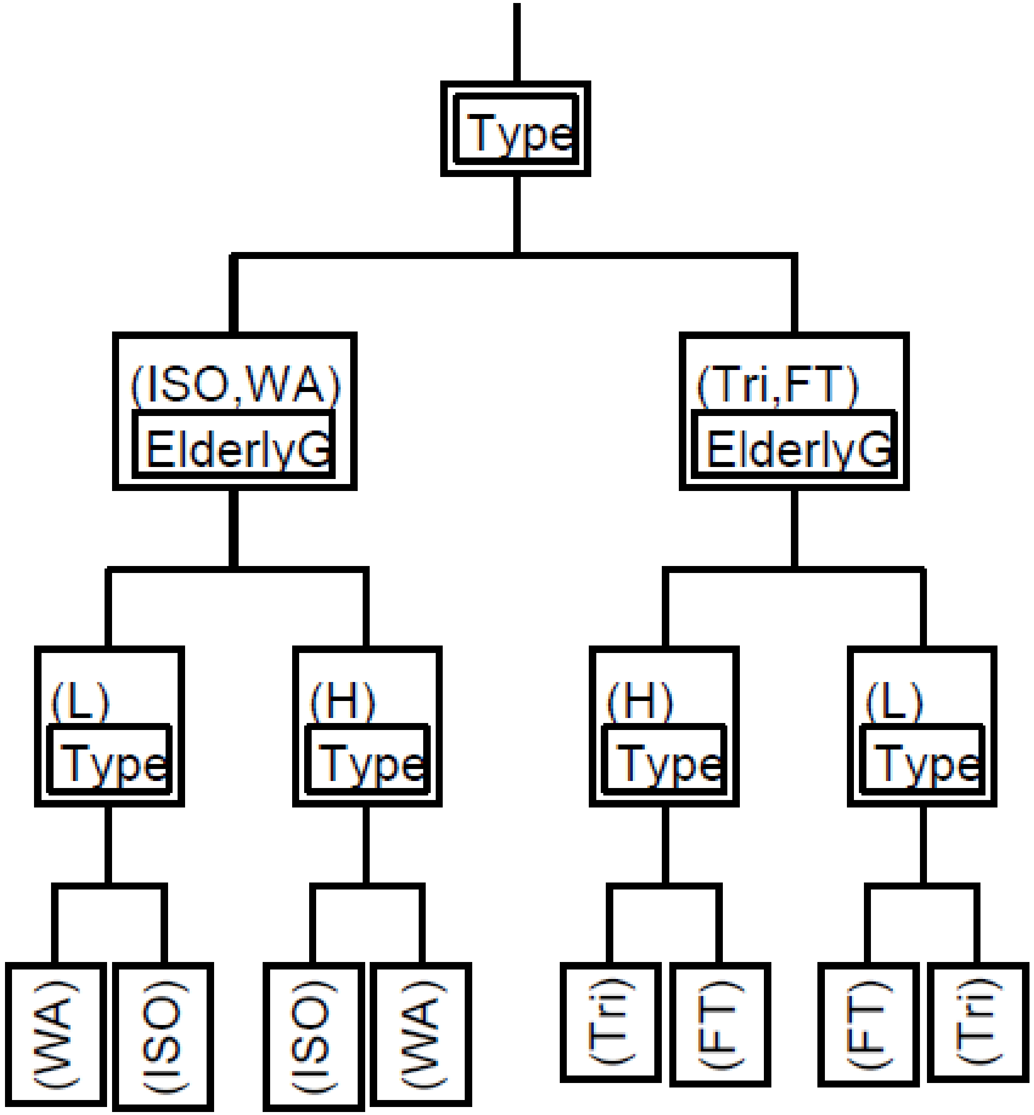
Ambulance



WithoutLetter

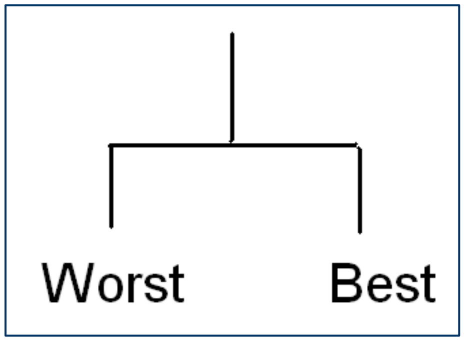
Identifying models that are more efficient in a given operational environment (CART)

Part 2: **DEA**



Conclusion:

Elderly is the most influential parameter for choosing an operating model



Conclusion and future research

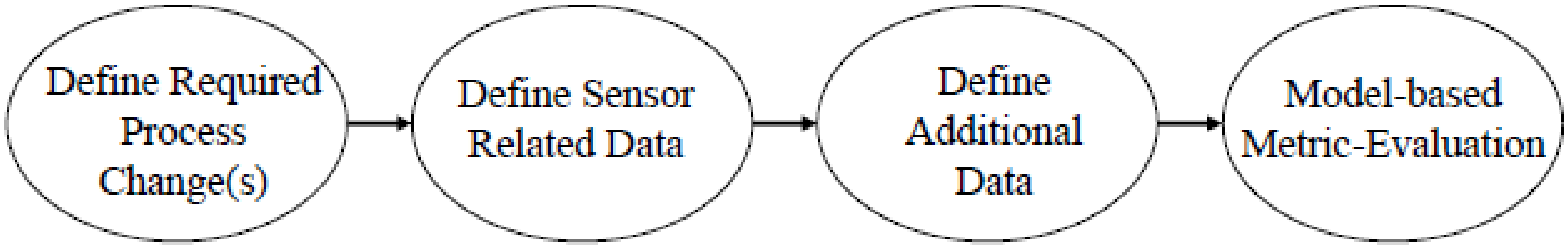
- There is no dominant operating model for all ED environments.
- EDs exposed to high volume of **elderly** patients, are most likely to need a different lane for high-priority patients (**FT** model).
- Other EDs (Low volume of elderly patients) can use a priority rule without the need for a distinguished space for high priority patients (**Triage** model).
- When Triage and FT are not feasible options (e.g. no extra nurse is available for Triage or place for FT) , it is recommended to differentiate lanes for Acute and Walking patient (**WA**).
- **Future Research:**
  - Adding operational models (e.g. **Output-based** approach and **Specialized-based** approach).

Part 3: long-term benefits of using real-time tracking (RFID) in the ED

Special thanks:
Prof. Shtub, Dr. Wasserkrug, Dr. Zeltyn
(M.D. Schwartz – ED Manager, Tzafrir – IT Head)

Goal

Present a multi-stage methodology to evaluate the potential benefits of introducing RFID technology, supported by examples of its application (operational, clinical, financial).



Methodology Steps

Step 1: Define required process changes

- We established a team of **physicians**, **operations managers**, and **IT experts**, at Rambam.
- We proposed **requirements** sorted into three categories: **operational** (reducing ALOS), **clinical** (high level of care), and **economical** (reducing abandonments without pay).
- We identify three process for evaluating the methodology:

1. Left without being seen (/ pay).
2. Long queues in the X-Ray.
3. Long queues in the CT.

Step 2+3: Define Sensor's and Additional Data

- CT: Implementing an alerting RFID system that helps reduce unnecessary waiting times, after a CT scan:
  - the time a patient completes his/her CT scan,
  - the time the patient has the CT scan results,
  - the patient's waiting time in excess of 10 minutes. (same with X-Ray)
- Using patients' RFID that prevents unregistered patient's abandonments, thus enhancing the hospital payment collection:
  - patient tag is near the hospital gate,
  - tag removed by non-approved personal.
- Two technologies to compare: Passive and Active

Step 4: Model-based Metric-Evaluation (Results)

The simulation results: comparing of different RFID systems

	Number of Exit Patients	LWBS	ALOS	$\sigma(LOS)$	$\sigma(ALOS)$
Without RFID	24,037	945(3.9%)	178.9	128.4	0.9
With Ideal RFID	24,118	0	184.2	133.6	0.7
With WiFi	23,987	475(2.0%)	186.8	133.9	0.9
With Passive RFID	24,087	0	177.2	128.9	0.7

Considering all three aspects (clinical, economical, operational), one is lead to prefer the **Passive RFID technology** which, in our context, yields the best overall performance (smaller ALOS, and less physician needed). Other hospitals might choose differently depending on specific preferences (for example, extra income from non-abandonments could be higher that the cost of adding physicians).

Thank you for your attention!