The Eleventh International Conference on Advances in System Simulation

SIMUL 2019

November 24 – 28, 2019 - Valencia, Spain

What is Simulation of Health Services providing?

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Universitat Autònoma de Barcelona

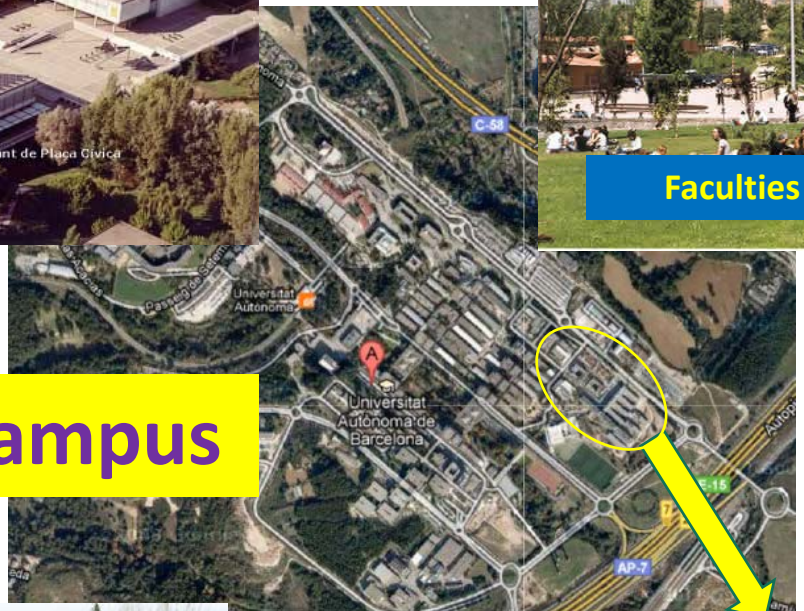
HPC4EAS Research Group

Computer Architecture Operating Systems

A comprehensive University

"Vila Universitaria" University Residence

Faculties



UAB Campus

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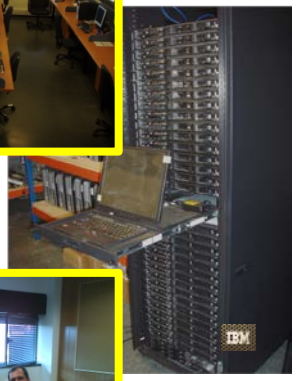

School of Engineering

The “Universidad Autónoma de Barcelona” (UAB) in figures

Summary of some of the most significant data of the UAB

https://www.uab.cat/web/about-the-uab/the-uab/the-uab-in-figures-1345668682835.html

- **57** Departments
- **25.924** Undergraduate students
- **4.663** Graduates-Degree holders
- **4.832** Students in Doctoral studies
- **>3.700** Foreign students (Graduate, master, PhD)
- **105** Undergraduate courses
- **579** Postgraduate and continuing education programmes
- **141** Official master's degrees
- **68** Doctoral programmes
- **541** PhD dissertations (2017-2018)
- **3.868** Teaching and research staff
- **569** Research staff in training
- **2.275** Administration and services staff
- **4.568** Articles published in indexed journals (Clarivate WoS-2018)

UAB Universitat Autònoma de Barcelona

Research Group

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Dr. Hugo Meyer
Dr. Ronal Muresano
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Dr. Cristian Tissera (UNSL)
Dr. Jorge Villamayor

http://grupsderecerca.uab.cat/hpc4eas/

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HPC4EAS Research Group

Parc Taulí Sabadell Hospital Universitari

Researchers of the “Simulation of Health Services” Team 2009 -2019

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Taboada, Manel

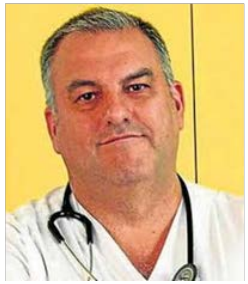
Stainsby, Hayden

Liu, Zhengchun

Rexachs, Dolores

Luque, Emilio

Epelde, Francisco



Antonin, Montserrat

Jaramillo, Cecilia

Shojaei, Elham

Bruballa, Eva

Vicente, Alex

Context: Social Impact

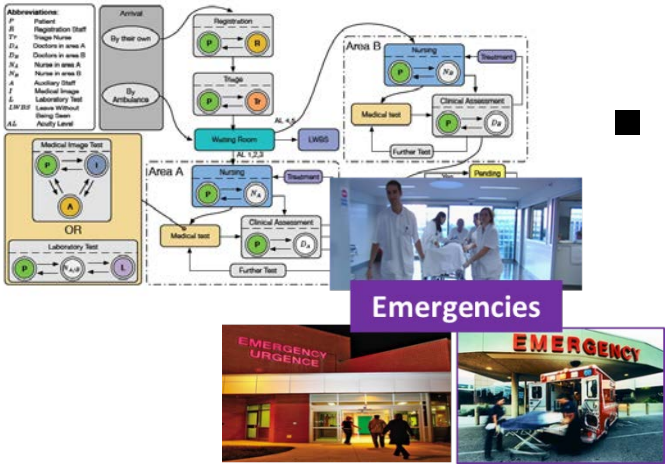
- ✓ **Growing demand for emergency medical care** (progressive growth of aging, increased life expectancy, greater number of chronic diseases, accessibility of emergency services, delay in scheduled care…).
- ✓ **Limitations on available resources** which determine the system's attention capacity.

Main consequences of the increase in patients entering the ED service

- Saturation of the service
- Increase in the total time a patient spends in the service (LoS)
- General discontent among patients
- Patiens being abandoned without receiving care (LWBS)
- Limited access to emergency care
- Increasing patient mortality

What is simulation offering?

- We “can” travel to the future through predictive simulation

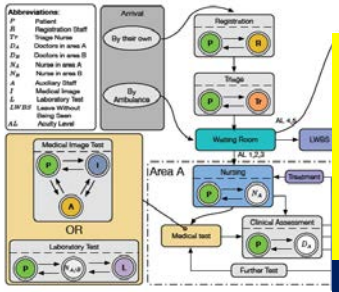


- We can discover the "potential" problems and then we return to the present time where…..

- We can try to avoid the "potential problems" seeking solutions

What is simulation offering?

- We “can” travel to the future through predictive simulation



We can bring DATA from THE FUTURE

and

use them with our DATA from THE PAST

"potential"

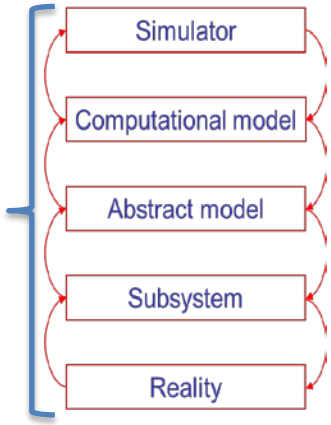
we return to

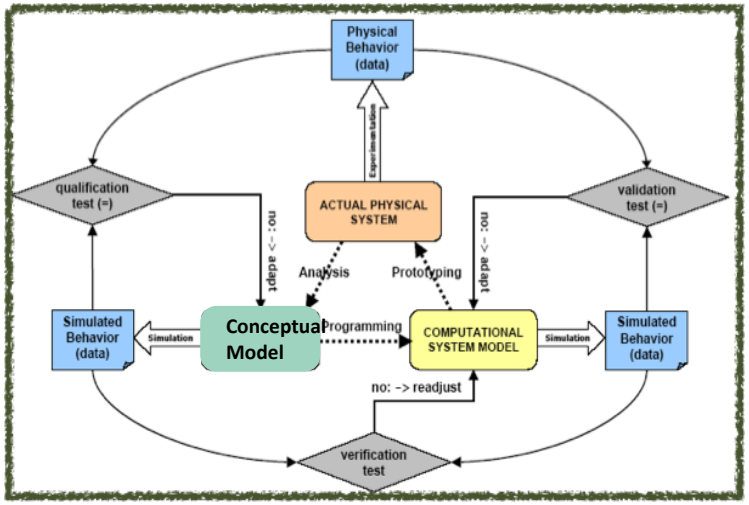
ere.....

- We car
problems" seeking solutions

SIMULATION OF COMPLEX SYSTEMS

Simulation represents a way to exploit a *computational model*

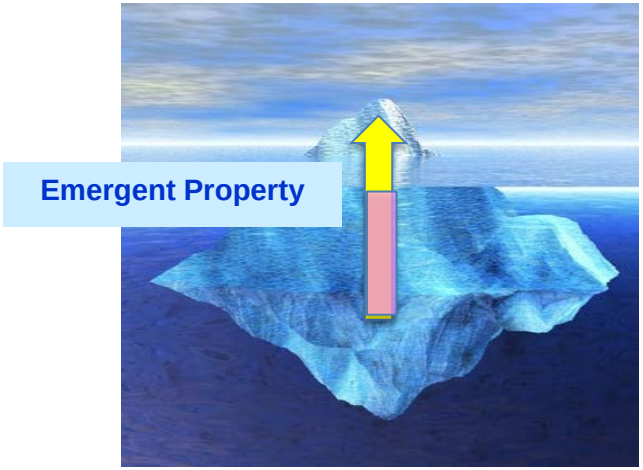




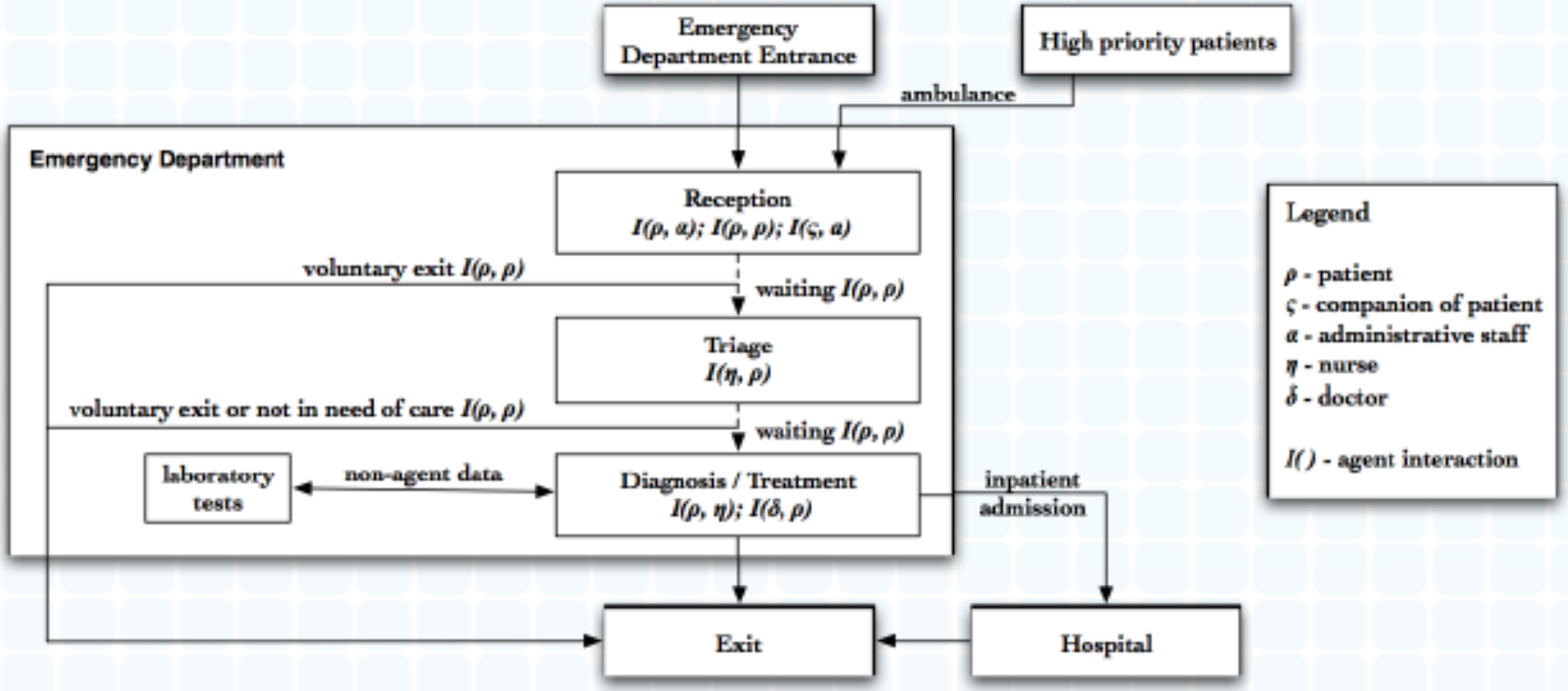
1.A **complex system** is one in which there are multiple **interactions** between many different **components**.
2.Based on low-level interactions among components, **emerge** collective high-level results.

The **Emergency Department (ED)** is a **Complex** Adaptive System
Model: Generalized and Adaptable **Agent Based Model (ABM)**

Emergent Property: an observation about a system that we might not anticipate from the separate study of its individual components
As the components of a system interact with each other, and influence each other through these interactions, the system as a whole exhibits **emergent behavior**
This characteristic makes the output of a system difficult to understand and predict.

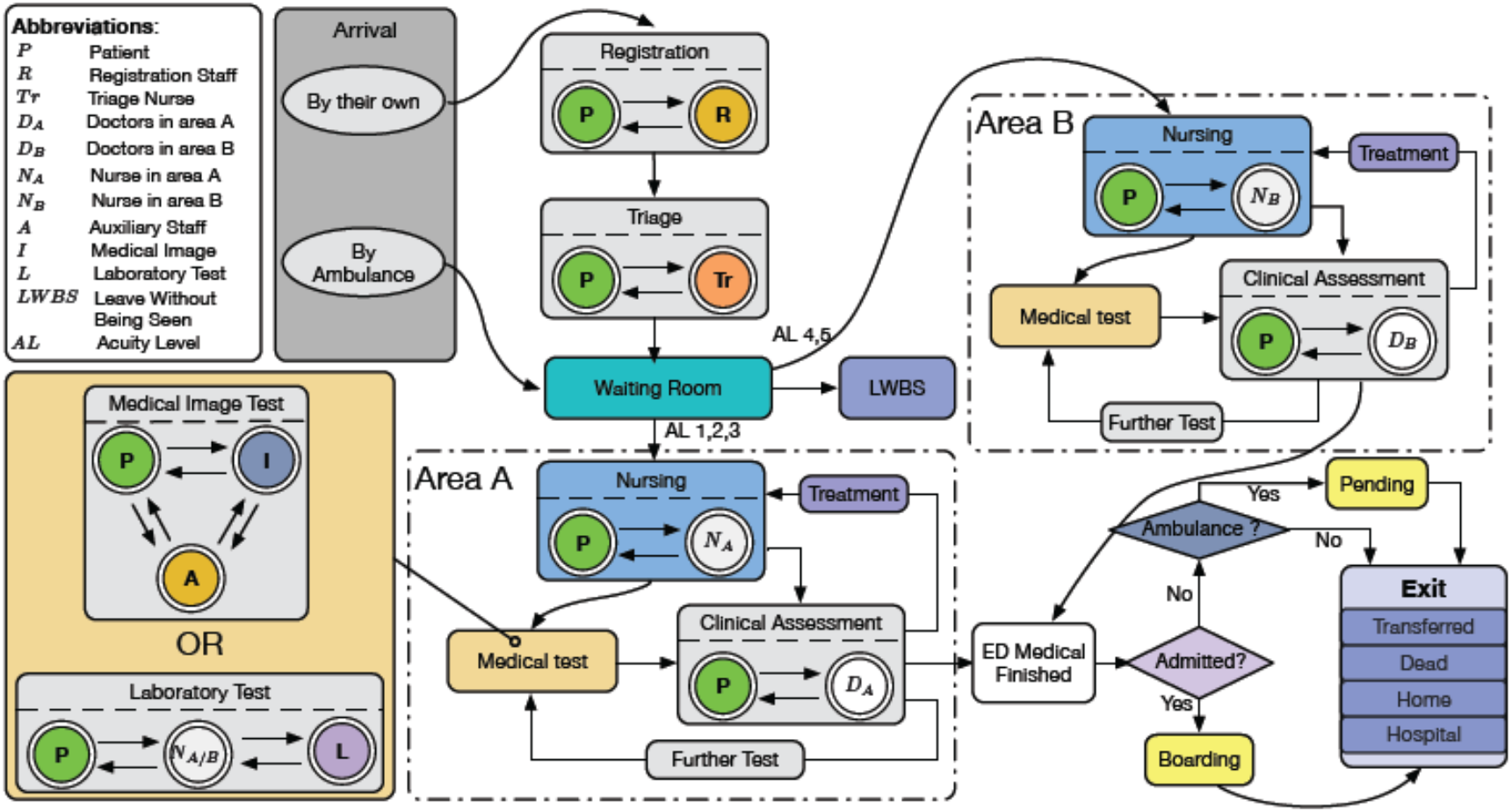


The First version of our Simulator



Hayden Stainsby, Manel Taboada, Emilio Luque:
Towards an Agent-Based Simulation of Hospital Emergency Departments. IEEE SCC 2009:

Conceptual Model of the ED Agent Based Simulator

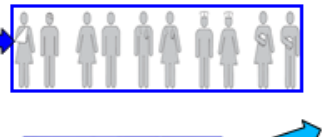


Emergency Department Simulation

The ED Model (Components)

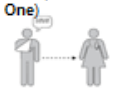
Kinds of agents

1) Active Agents	2) Passive Agents
Patients	Information system
Companions of patients	Loudspeaker system
Admission personnel	Pneumatic pipes
Sanitarian technicians	Tests services
Nurses (Triage, Emergency)	
Doctors (Emergency, Specialists)	



Communication Model: 3 different types

1 to 1(One-to-One)



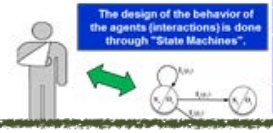
1 to n (Multicast)

1 to Zone: individuals in Zo
(Area- Restricted Broadca

The ED Model (Individual model)

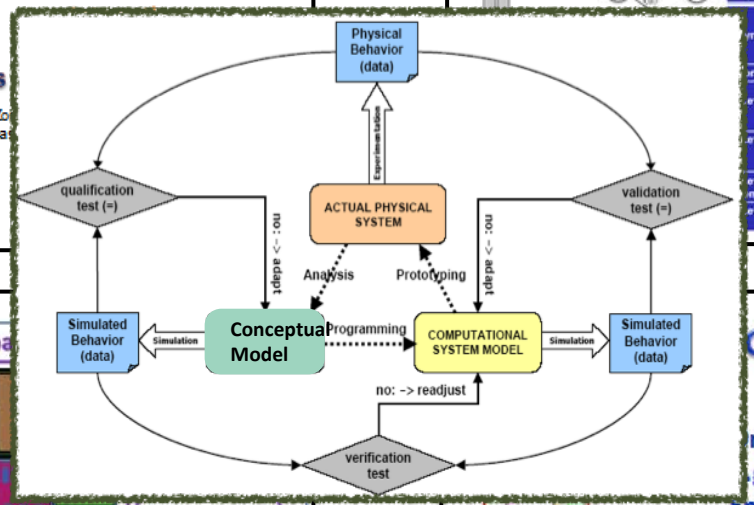
Agent/Individual Model

The design of the behavior of the agents (interactions) is done through "State Machines".

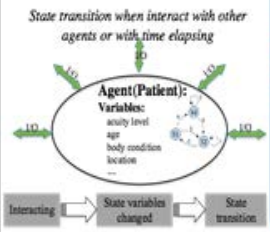


State variables

STATE Variables	Values	Observability
Name/identifier <id>	Unique per agent	I
Personal details	Gender, Medical history (cardiology, pulmonology, neurological,...); Allergies (yes-no); Treatments that received (classified into therapeutic groups: bronchodilators, vasodilators, etc.); Origin (national or immigrant)	I
Location	Entrance, Admissions, Waiting Room, Triage, Treatment Zone.	E
Action	Idle, Requesting information from <id>, Giving information to <id>, Searching, Moving to <location> , Waiting for ambulance.	E
Physical condition	Healthy; Hemodynamic-Constant; Barthel Index (degree of dependence).	E/I/N
...mptoms (patients)	Healthy, Cardiac/respiratory arrest, severe/moderate trauma, headache, vomiting, diarrhea	E/I
...mmunication skills	Low, Medium, High	E
...evel of experience (doctors)	Resident (1 to 5); Junior (5-10); Senior (10 - 15) and Consultant (over 15 years)	E/I
...evel of experience (triage nurses)	Low, Medium, High	E/I
...evel of experience ...mergency nurses)	Low, Medium, High	E/I
...evel of experience (admissions)	Low, Medium, High	E/I



All together



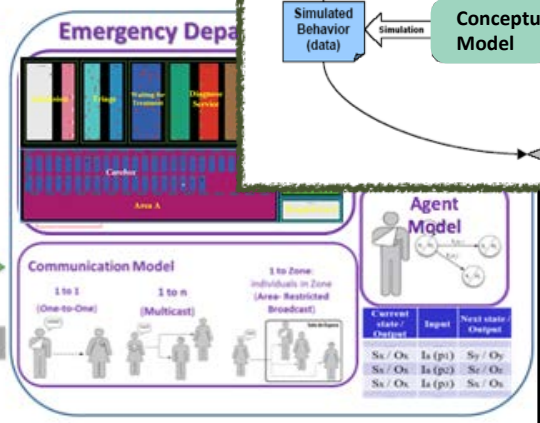


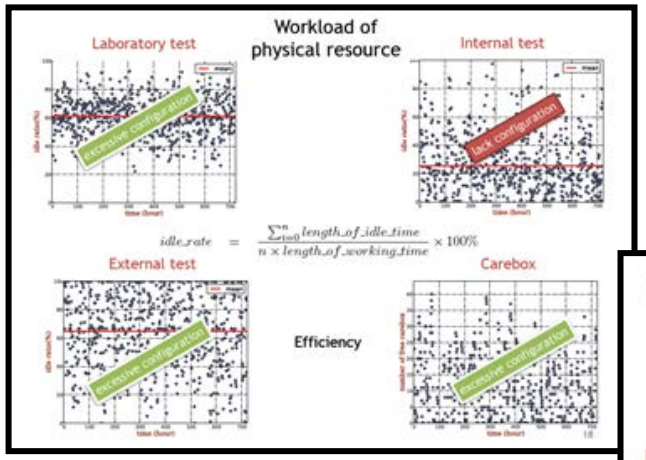
Table 1: A PART OF A NURSE'S STATE TRANSITION.

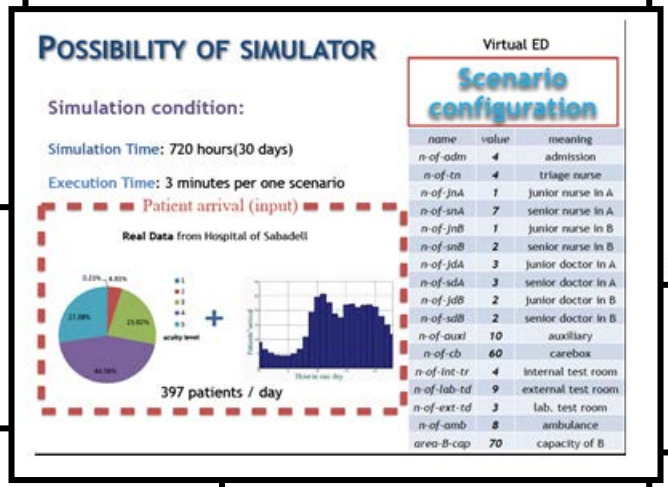
State index	Source State	Destination state	Input
...	...	...	...
S_t	Waiting for task.	Meet with patient(take blood sample).	blood test task from IS
S_{t+1}	Meet with patient.	Waiting for task.	sample take finished
S_{t+2}	Waiting for task.	Meet with patient(for treatment)	treatment task from IS.
S_{t+1}	Meet with patient.	Waiting for task.	treatment task finished
S_{t+3}	Waiting for task.	Meet with patient(help discharging)	Discharging task from IS.
...	...	...	...

...odel (Layout)

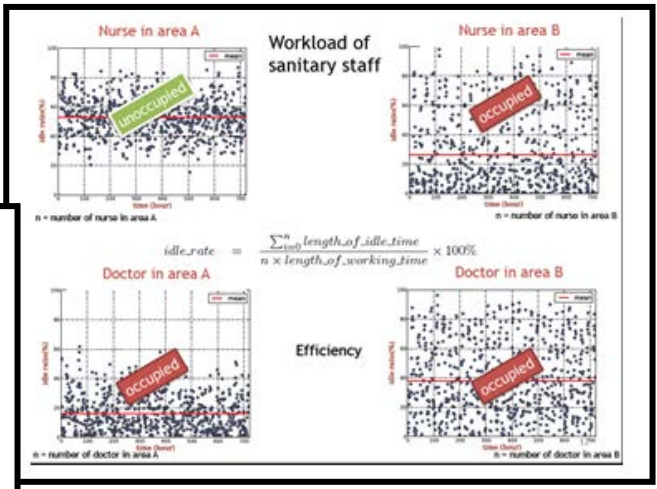
...ne Typical ED in Spain
...g. Parc Tauli Hospital
Emergency Service

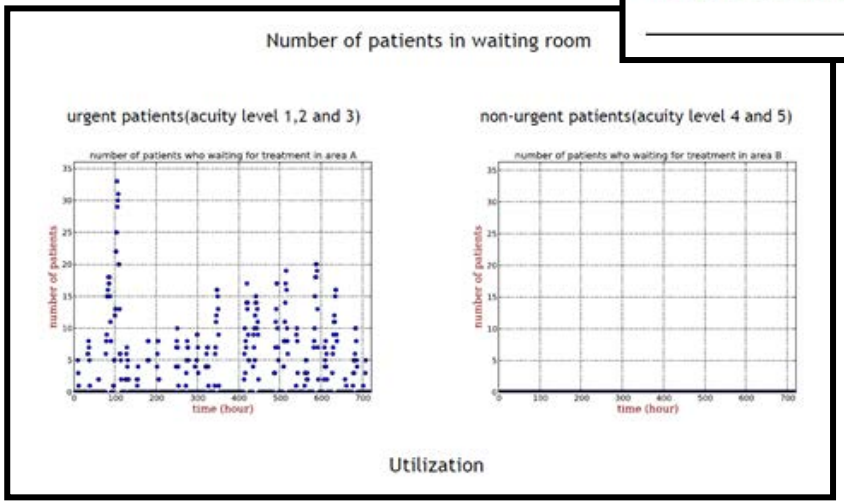
Results of the Simulation of the Emergency Department

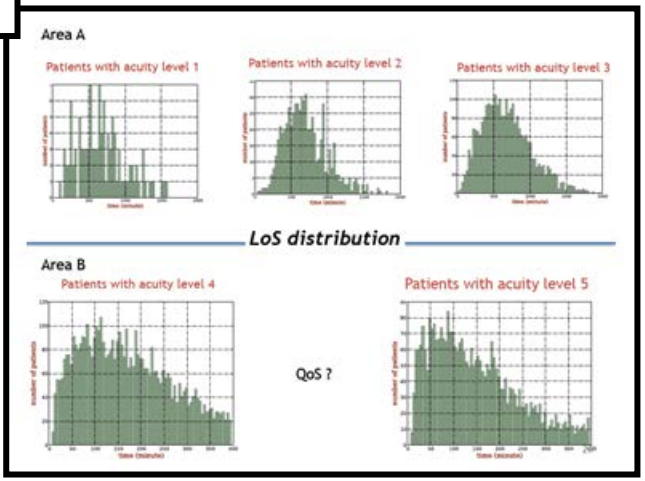




name	value	meaning
n-of-odm	4	admission
n-of-tn	4	triage nurse
n-of-jnA	1	junior nurse in A
n-of-snA	7	senior nurse in A
n-of-jnB	1	junior nurse in B
n-of-snB	2	senior nurse in B
n-of-jdA	3	junior doctor in A
n-of-sdA	3	senior doctor in A
n-of-jdB	2	junior doctor in B
n-of-sdB	2	senior doctor in B
n-of-auxl	10	auxiliary
n-of-cb	60	carebox
n-of-int-tr	4	internal test room
n-of-lab-td	9	external test room
n-of-ext-td	3	lab. test room
n-of-amb	8	ambulance
area-B-cap	70	capacity of B







What is Simulation of Health Services providing?

- "Visiting the future" and taking decisions
- Simulation as a source of data
- Impossible/forbidden experiments
- Virtual Clinical Trials

Those that Simulation of Health Services gives us

- ✓ **“Visiting the future” and taking decisions**
  - Simulation as a source of data
  - Impossible/forbidden experiments
  - Virtual Clinical Trials

MANAGING PROBLEMS

Managerial decisions

and

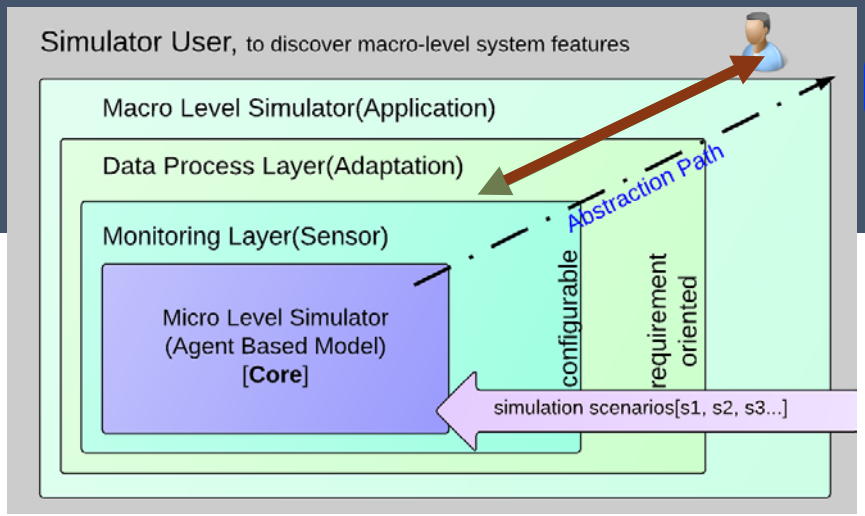
medical decisions

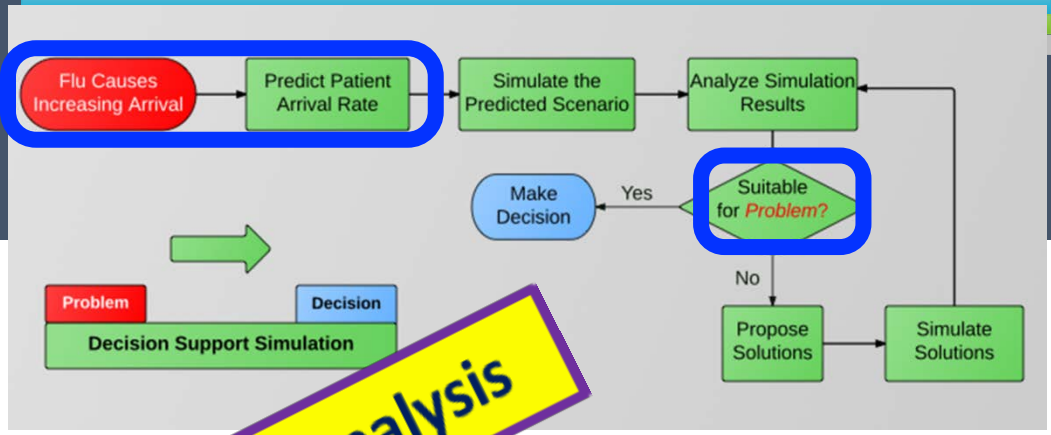
In the functional management we must take decisions to answer questions of this kind:

Using Simulation

- If the number of arrival patients doubled, what will happen?
- If we increase 20 more boxes, the overcrowding could be solved?
- The budget decreased, how the QoS will be affected?
- Which technical staff should be reduced? doctors? nurses? ... ?

How can we know and **evaluate** the **effect of a decision** without the commitment of any physical resources or interruption of the system?





Problem Detection: Model Based Data Analysis

Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)			
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
361	10.83	10.30	9.79	3.01			67.94	53.95	43.68
397	10.84	10.90	10.41				46.31	78.29	62.05	50.27
416	11.66	11.28				83.64	48.01	80.59	64.23	52.16
436	11.87	11.73				86.75	50.01	84.50	66.84	54.17
456	11.71				**8.94**	**91.32**	51.85	87.19	69.80	56.27

Add 2 mo ans or analysis machines to laboratory room

Daily	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
456	11.58	11.90	11.70	3.65	**3.17**	**60.67**	1.99	87.19	69.47	56.65
476	12.54	12.70	14.33	3.80	3.57	64.19	55.04	92.30	73.01	59.42
496	13.23	12.90	**33.93**	4.02	4.16	66.37	56.90	**96.06**	76.32	62.25

Add two more doctors to area A

Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
496	10.89	11.01	**11.07**	3.98	4.15	66.73	57.50	**71.84**	75.79	61.58
516	11.12	10.86	11.20	4.13	4.79	68.75	58.67	72.99	78.80	64.30
535	11.26	11.31	12.54	4.36	5.82	71.39	60.65	76.00	82.52	67.14

Final Decision:
add Two Laboratory **Technicians or Analysis Machines**
and
Two **Doctors** to area A
For
150% extra arrival

Influence of Ambulance Service for Departure

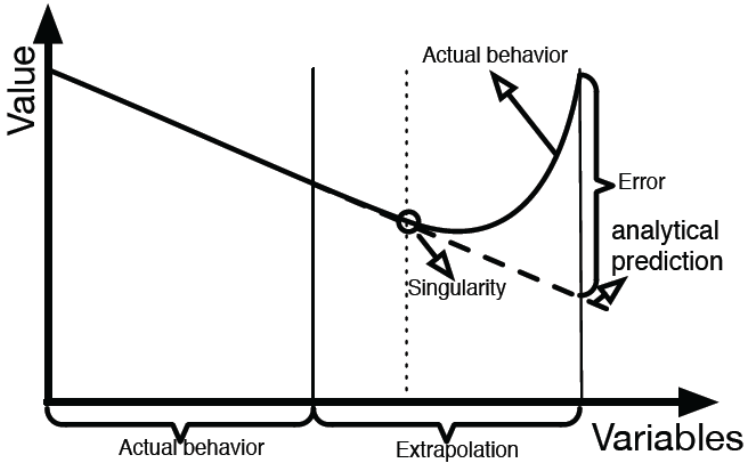
✓ (one way to relieve overcrowding in real situation);

Table 6: Influence of ambulance response time to LoS.

Ambulance response time model	Average LoS by acuity level(hour)				
	1	2	3	4	5
current actual delay(*mean*=63 minutes)	13.23	12.90	**33.93**	4.02	4.16
50% of actual delay(*mean*=31 minutes)	12.70	12.60	**17.96**	3.94	4.03
without delay	12.04	12.51	**15.53**	3.86	3.86

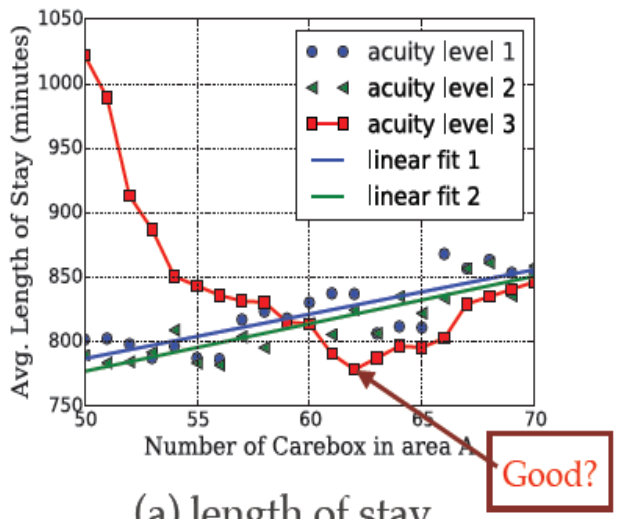
Emergency Department Overcrowding

The emergency department system is **overcrowding**,
WHAT-IF
we add 20 careboxes to the system?

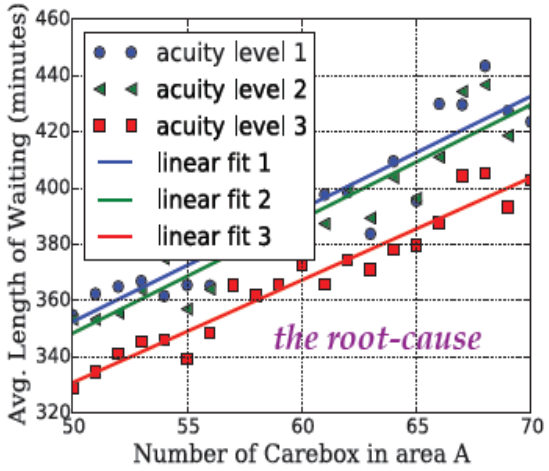


Every decision we take is based on information, stop guess.

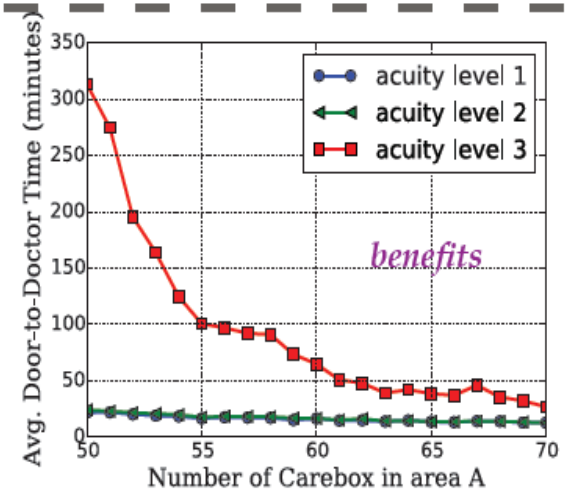
Overcrowding: Influence of additional careboxes on patients' attention (Area A)



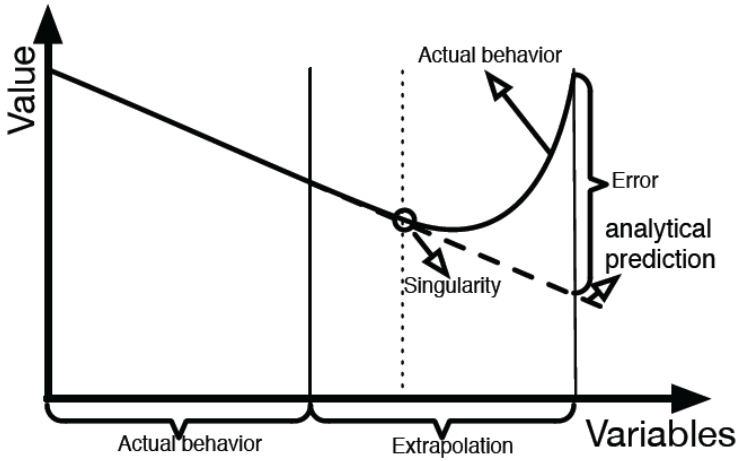
(a) length of stay



(b) length of waiting time (in treatment area)



(c) door-to-doctor time



Mitigating overcrowding in emergency departments by schedulig non-critical patients admission

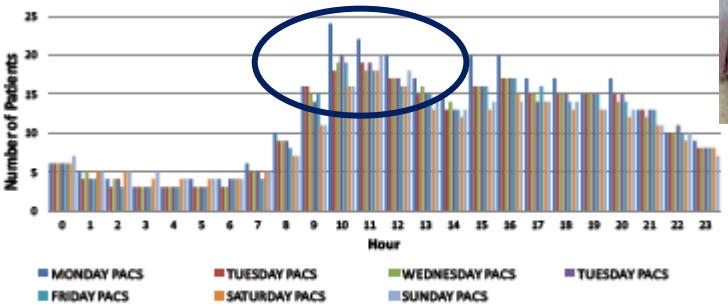
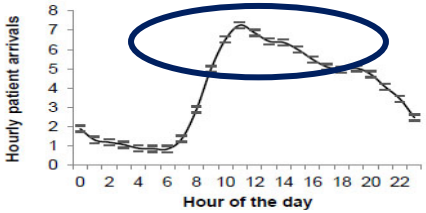
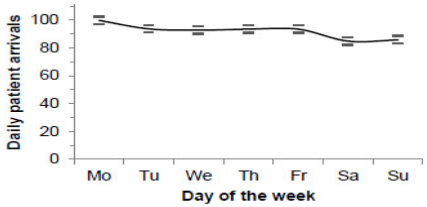
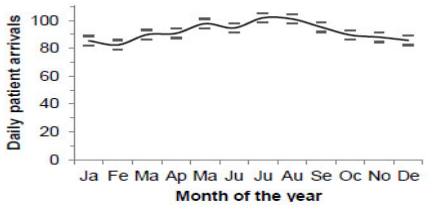


Figure 1. Input pattern of patients per hour and day of the week (historical data of 2014 of the Hospital de Sabadell).







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Schedulig model for non-critical patients admission into the ED

HISTORICAL DATA

Patients Input Distribution (number and level)

Test and Treatment Probability Distribution

System State (SS) calculation (Number of patients in care in each hour)

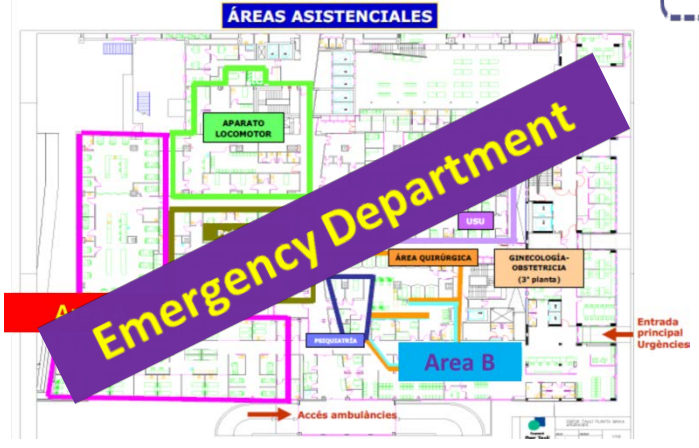
PATIENTS RELOCATION

Limit of attention capacity (T_ThP)
Constraint of maximum delay time

SS UPDATE for each relocation

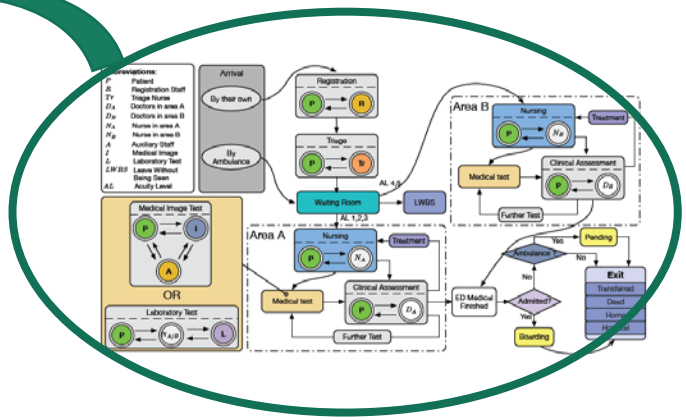
CURRENT DEMAND OF SERVICE

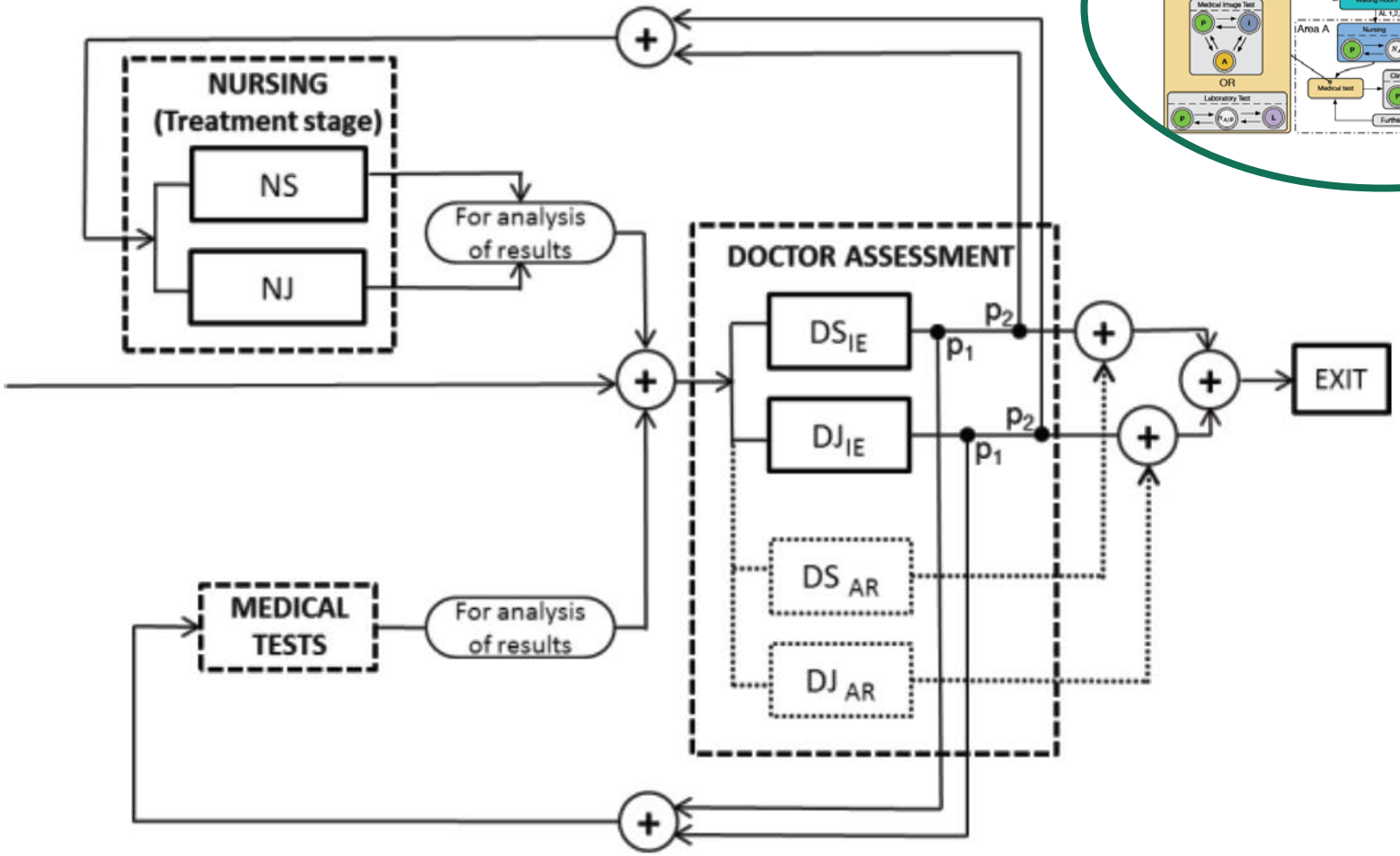
APPOINTMENT SCHEDULING FOR PATIENTS ADMISSION



HPC4EAS Research Group

Model of “Patient Flow” in diagnosis & treatment phase





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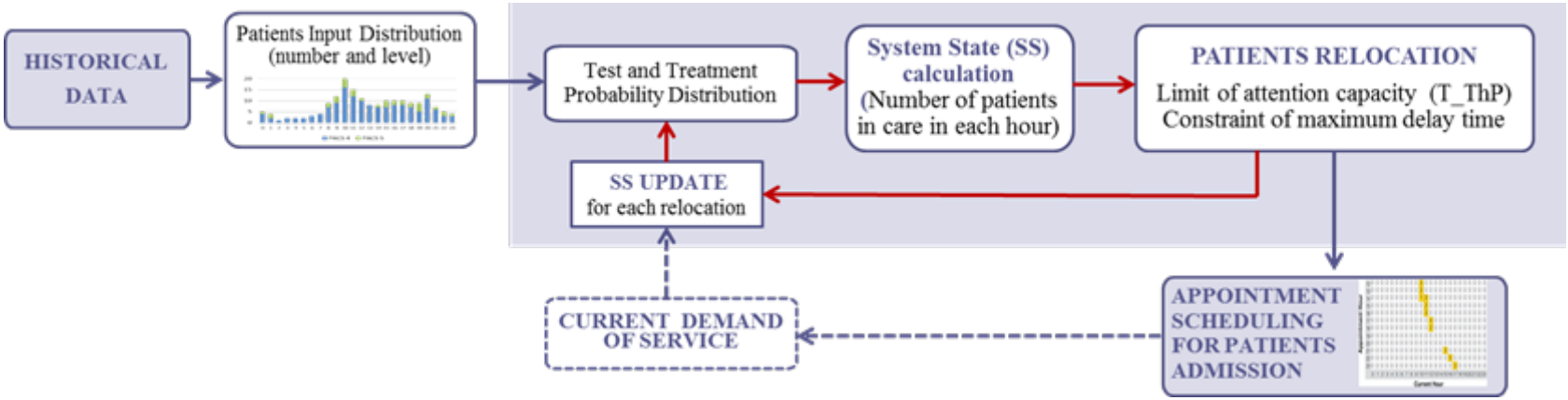
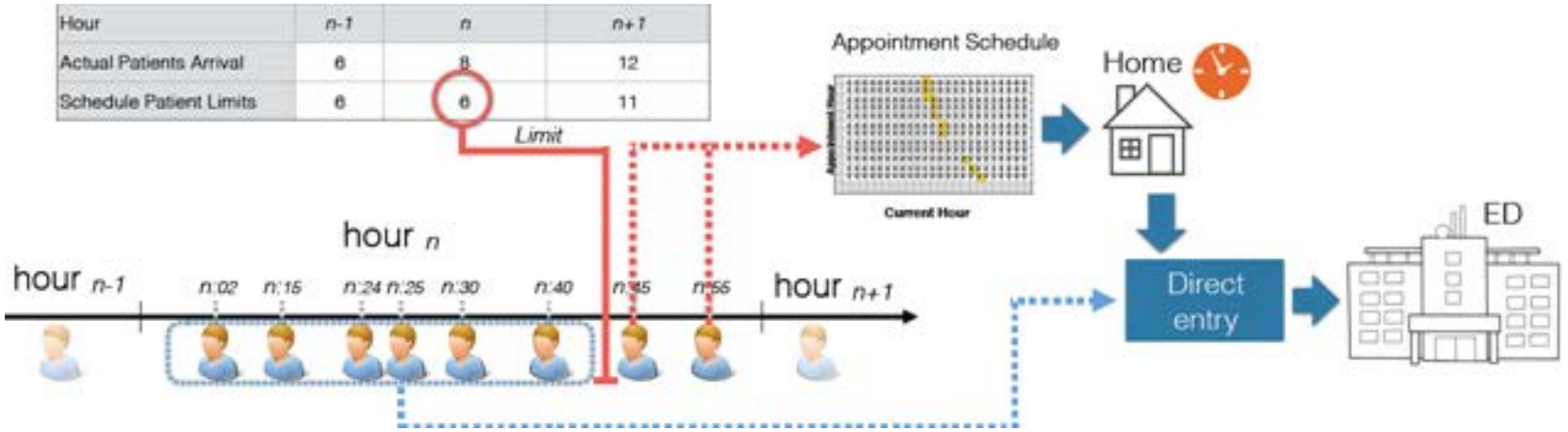
Scheduling Model For Non-critical Patients Admission Into A Hospital Emergency Department



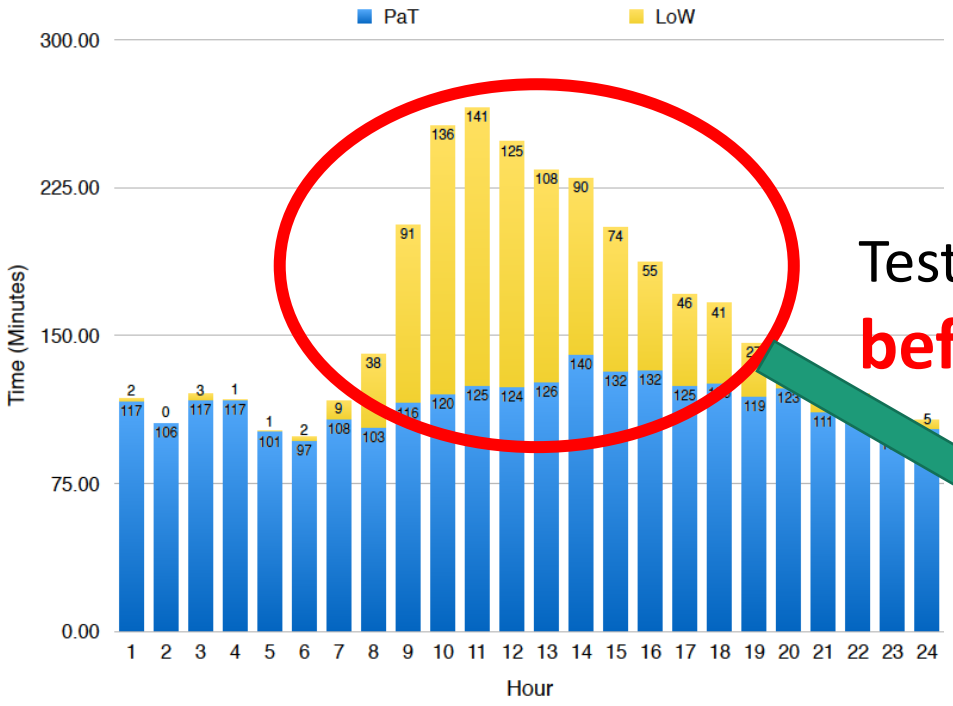
Scheduling model for non-critical patients admission into the ED



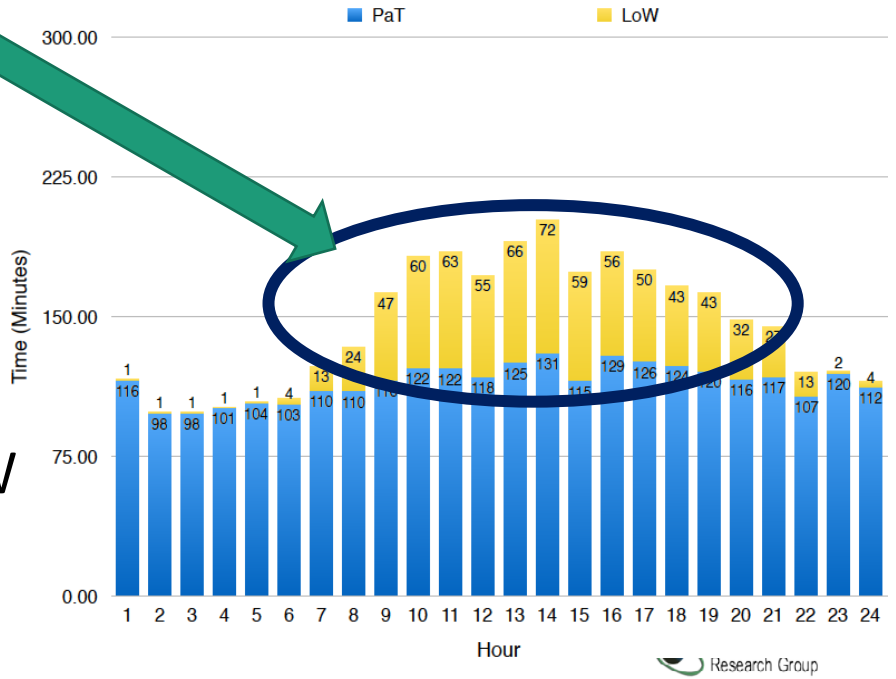
Recommendation system for non-critical patients admission into the ED

Results of Non-critical Patients Admission Relocation into A Hospital Emergency Department

PaT: Patient attention Time
LoW: Length of Waiting



Test Patients PaT and LoW
before patients relocation



Test Patients PaT and LoW
after patients relocation

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Those that Simulation of Health Services gives us

- "Visiting the future" and taking decisions
- ✓ **Simulation as a source of data**
- Impossible/forbidden experiments
- Virtual Clinical Trials

When Big Data Isn't Enough (Michel Morvan COSMOTECH)

While a big data approach does work in many instances, there are some cases where it will fail to deliver solution:

- The **first limit** is that big data is designed to predict phenomena that have **happened before**
  - That **limits** its **usefulness for predicting unusual events** that we know can happen but which are not expressed in the data.
- The **second limitation** of the big data approach is that it's largely a **black box**.
  - The algorithms will find many correlations and use them to make predictions about what will happen in the future.
  - Data tells us **what** but not **why**: "You cannot explain the why". "In some cases, this is OK. But in other cases…you really need to explain why they're going to happen that way."

Alex Woodie. https://www.datanami.com/2017/01/26/big-data-isnt-enough/

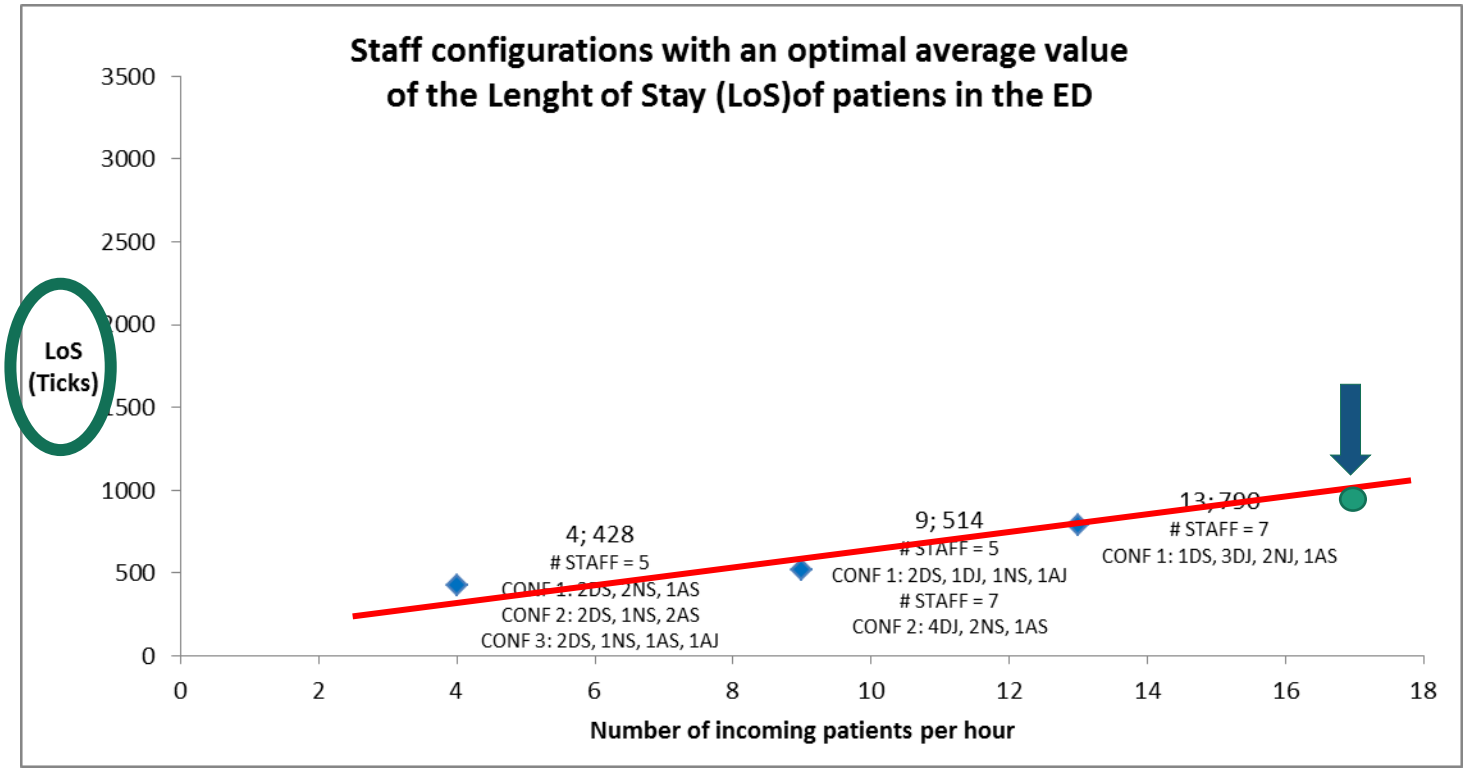
Simulation as a source of data for unusual and unexpected situations in Health Services

- The use of data mining techniques, based on real data provided directly by health services, provides new useful knowledge for decision-making but **not always real data are available for all possible situations,**

- Simulation provides parametrizable tools (simulators) allowing us to "**replicate/create**" any possible situation, becoming then the simulator in a **"sensor/generator" of "virtual-data",** otherwise difficult or impossible to obtain from real systems or historical data bases.

- **"Simulated-data" will expand "real-data"**, allowing us obtaining more reliable models better predictions and more powerful and reliable support for helping Decision Support Systems..

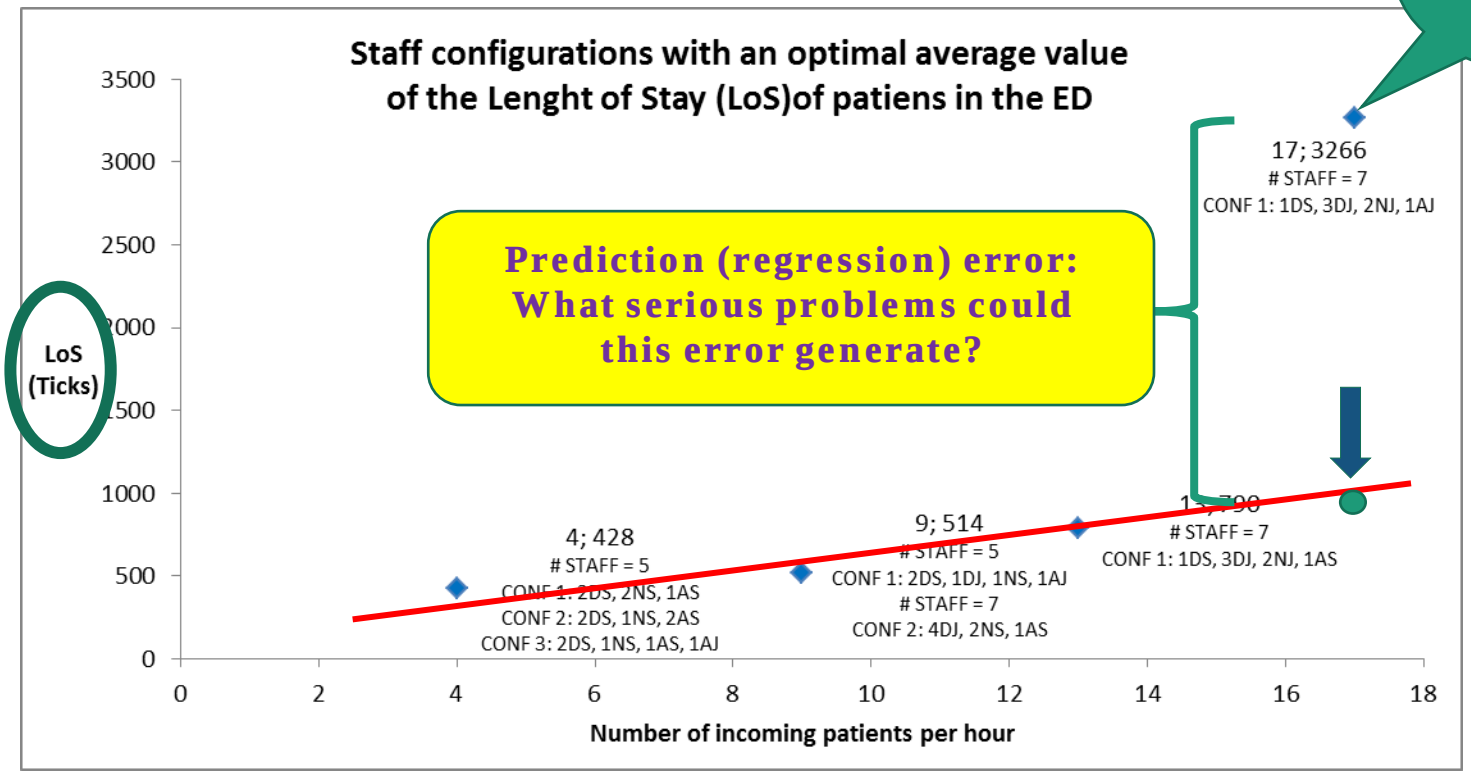
Predicting with Real Data



Incoming Patients	4 pat/h 9 pat/h 13 pat/h 17 pat/h

Predicting with Real Data

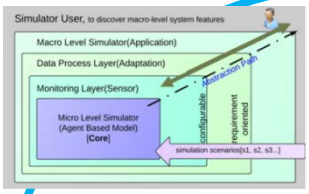
+ SIMULATION DATA: IMPROVING PREDICTION



Data generated by simulation can be a more reliable source for predicting the behavior of the real system.

Incoming Patients
4 pat/h
9 pat/h
13 pat/h
17 pat/h

Simulation (Virtual) and Real Data



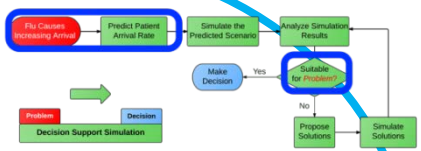


Table 1: LoS and ED resources utilization with increasing arrival patient

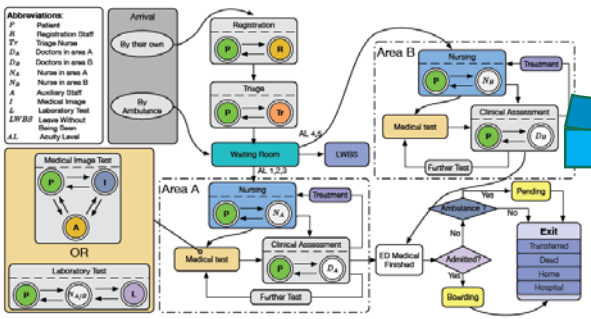
Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
361	10.83	10.90	9.79	3.01	2.81	70.51	40.57	67.94	53.95	43.68
397	10.84	10.90	10.41	3.43	3.81	81.39	46.31	78.29	62.05	50.27
416	11.66	11.28	10.69	3.59	4.12	83.64	48.01	80.59	64.23	52.16
436	11.87	11.73	11.31	3.78	5.28	86.75	50.01	84.50	66.84	54.17
456	11.71	12.09	11.85	3.98	**8.94**	**91.32**	51.85	87.19	69.80	56.27

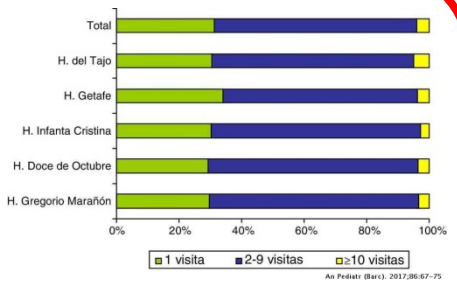
Add two more technicians to laboratory room

Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
456	11.58	11.90	11.70	3.65	**3.17**	**60.67**	51.99	87.19	69.47	56.65
476	12.54	12.70	14.33	3.80	3.57	64.19	55.04	92.30	73.01	59.42
496	13.23	12.90	**33.93**	4.02	4.16	66.37	56.90	**96.06**	76.32	62.25

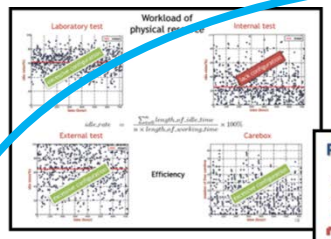
Table 1: Two more doctors added to area A

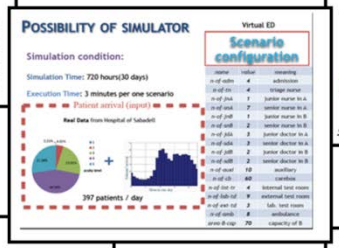
Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
	1	2	3	4	5	Tr_{lab}	N_A	D_A	D_B	N_B
496	10.89	11.01	**11.07**	3.98	4.15	66.73	57.50	**71.84**	75.79	61.58
516	11.12	10.86	11.20	4.13	4.79	68.75	58.67	72.99	78.80	64.36
535	11.26	11.31	12.54	4.36	5.82	71.39	60.65	76.00	82.52	67.14

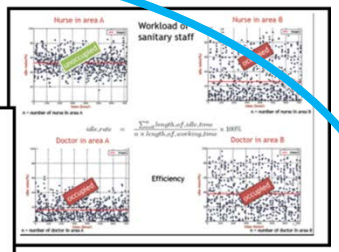


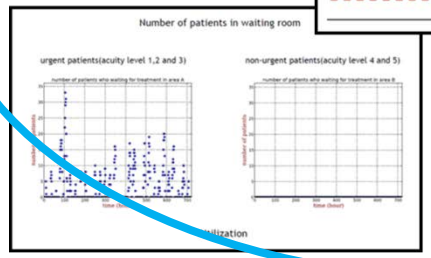


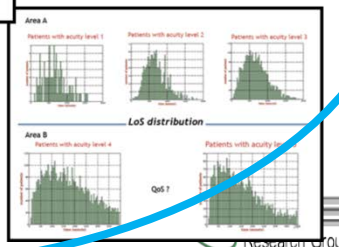
Patient Frequency











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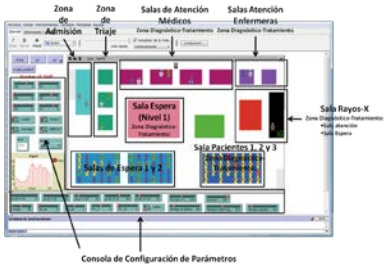
Our proposal: inclusion of the 5th V Virtual data (simulation generated)

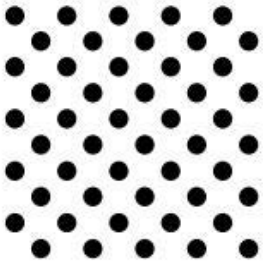
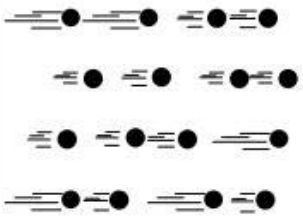
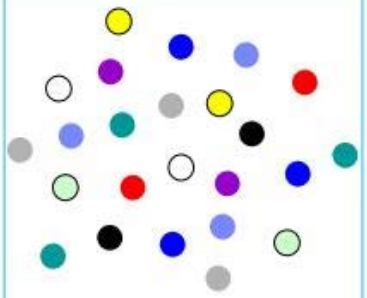
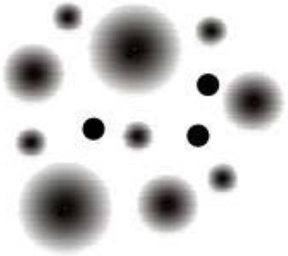
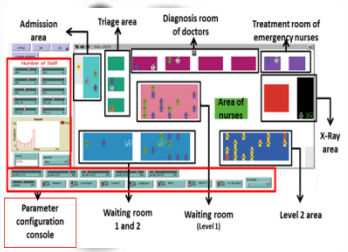
The promise of Big Data

- Data contains information of great value
- If you can extract those insights you can make far better decisions…but is data really that valuable?



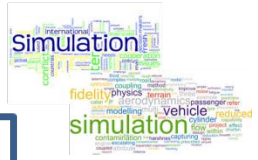
The simulator: source of Big Data

Simulation

Volume	Velocity	Variety	Veracity*	Virtual
				
Data at Rest	Data in Motion	Data in Many Forms	Data in Doubt	Data from "Virtual Worlds"
Terabytes to exabytes of existing data to process	Streaming data, milliseconds to seconds to respond	Structured, unstructured, text, multimedia	Uncertainty due to data inconsistency & incompleteness, ambiguities, latency, deception, model approximations	Simulation as a sensor of the real world

INNOVATION

Big Data and Simulation



Without simulation

Real Data → (Data Mining Analytics) → **Relations Knowledge** → (Extrapolation) → **Relations Knowledge** } **Extrapoled**

Data obtained directly from the real system will be complemented with data **generated by the simulator.**

What would be more reliable?

Including simulation

Real Data + **Simulated Data** → **Extended Data** → (Data Mining Analytics) → **Relations Knowledge** } **Extended**

Models → (Simulation)

The simulator as a sensor of "real data" difficult or impossible to be obtained

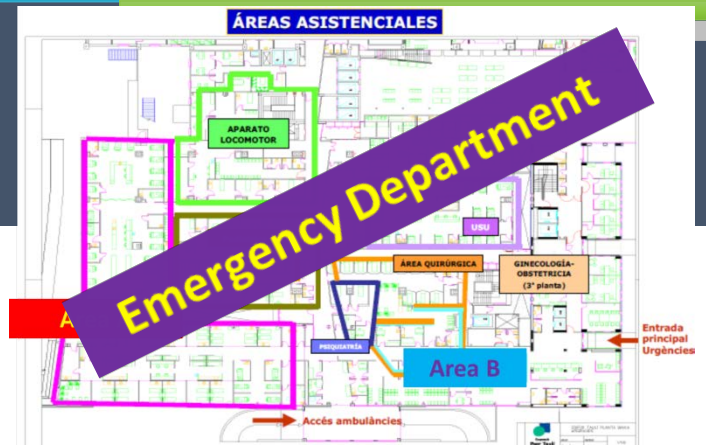
"Simulation as a Sensor of Emergency Departments: Providing Data for Knowledge Discovery" (Work-in-Progress Paper) E. Bruballa, M. Taboada, E. Cabrera, D. Rexachs, E. Luque. Procc. *SIMUL 2014 : The Sixth International Conference on Advances in System Simulation pp 209-212. 2014*

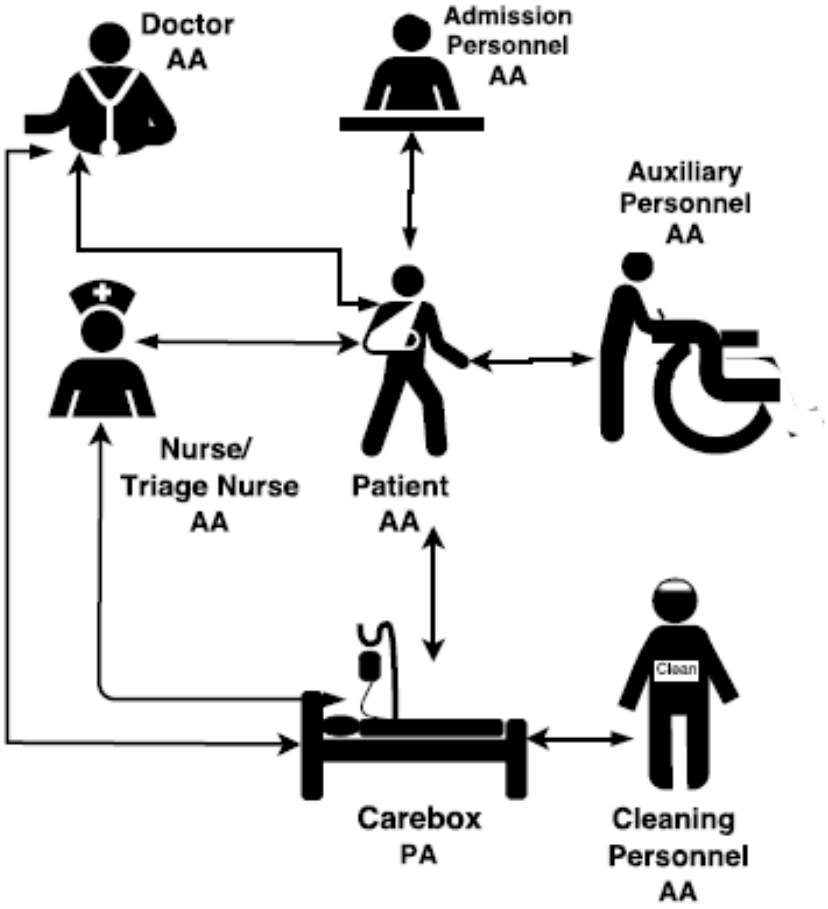
"Simulation and Big Data: A Way to Discover Unusual Knowledge in Emergency Departments" (Work-in-Progress Paper) E. Bruballa, M. Taboada, E. Cabrera, D. Rexachs, E. Luque. Procc. *2014 International Conference on Future Internet of Things and Cloud. pp 367-372. 2014*

Those that Simulation of Health Services gives us

- "Visiting the future" and taking decisions
- Simulation as a source of data
- ✓ **Impossible/forbidden experiments**
- Virtual Clinical Trials

Contact Transmission Model of the MRSA propagation in the Emergency Department





Possible infectious states

Patient
- **Susceptible (S):** Not carrying MRSA
- **Colonized (C):** Carrying MRSA without symptoms.
- **Infected(I):** Carrying MRSA with symptoms.

HCW
- **Susceptible (S):** Not carrying MRSA
- **Permanent Colonized (PC):** Carrying MRSA. always. Not symptoms. If decolonization time finish return to S.
- **Temporarily Colonized (TC):** Carrying MRSA. Return to S with an effective hand disinfection action.

Carebox
- **Uncontaminated:** Not MRSA.
- **Contaminated:** has MRSA. Return to uncontaminated state after clean action.

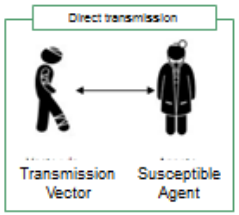
AA = Active Agent
PA = Passive Agent
↔ = Interaction

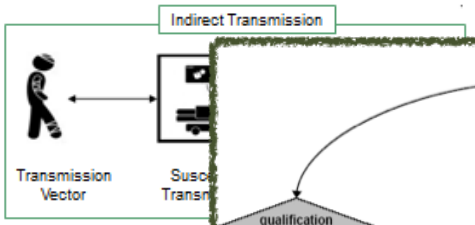
Simulation of the MRSA propagation in the Emergency Department

Modelization: Transmission forms

Physical contact.

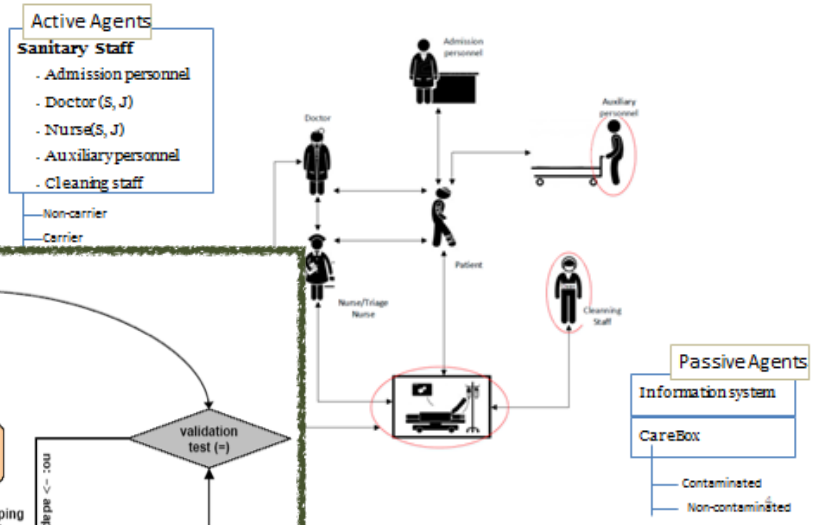
- **Direct transmission** => Active agent – Active agent
- **Indirect transmission** => Active agent – Passive agent– Active agent

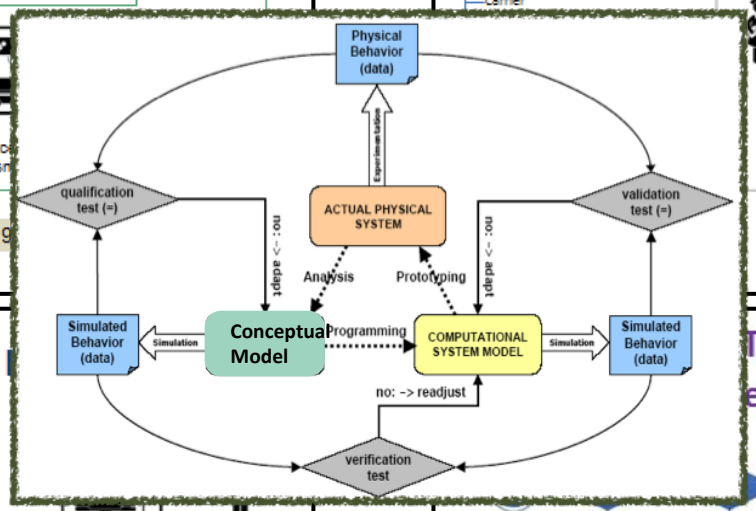




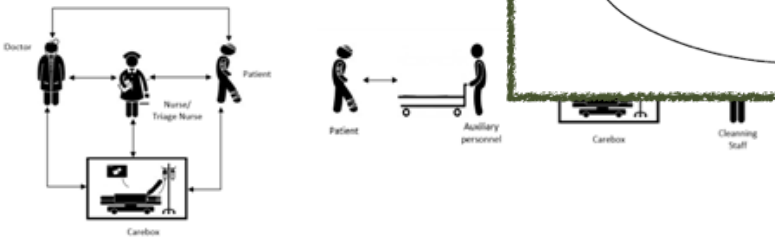
MRSA Time life on dead surfaces: 9

Contact Propagation Model: Agents





Contact Propagation Model: I



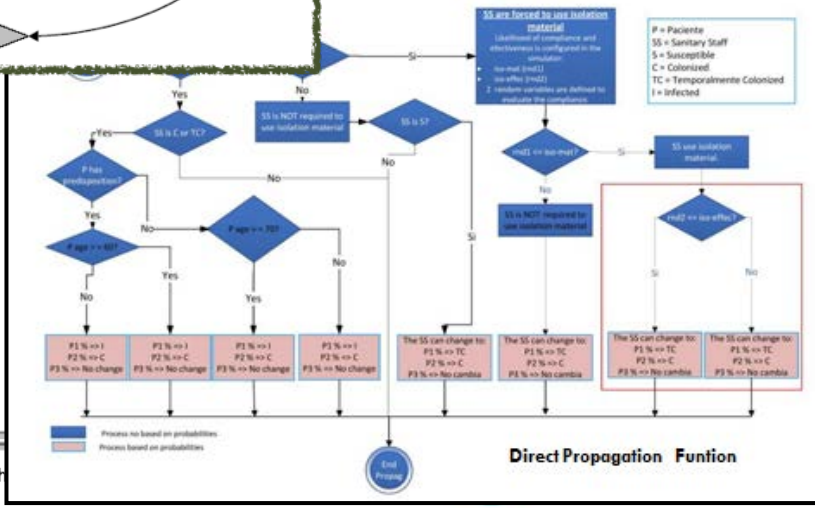
Prevention policies of the healthcare staff

The accomplishment level of the healthcare staff agents with the prevention policies is measured by the accomplishment factor (AF).

The three prevention actions that are evaluated in this research are:

- Handwashing
- Sanitizing hand
- Use of isolation material

Transmission Model: e MRSA propagates



Simulation: Case Study A

Objetive: To identify the influence of **hand washing (HW)** on the number of infected and colonized patients considering different values of effectiveness.

Parameters of Execution:

Description	Variable	Value
Simulation Time	Simul_Time	1440 hours
Average patient arrive per day*	Averag_Pat	398
Percentage transmission vector that arrive ED	Percen_TV	2%
Percentage of patient with predisposition to acquire MRSA	Percen_Predis	20%
Hand wash probability	HandW_Prob	100%

*The flow of patients has a probability distribution per hour, considering hospital data.

Output dates:

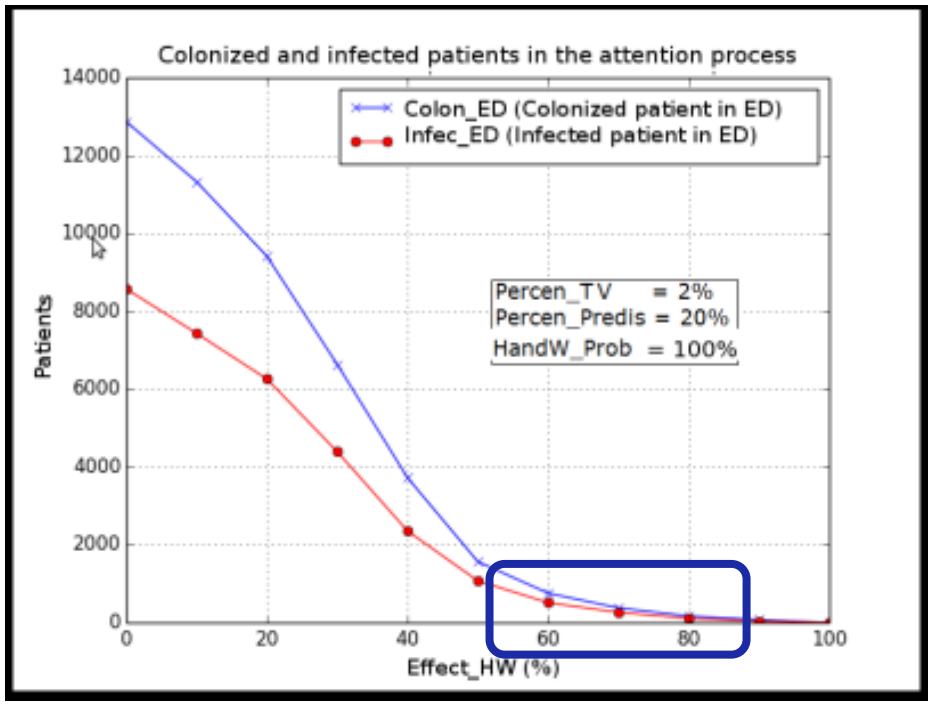
Table : Handwash Probability = 100%

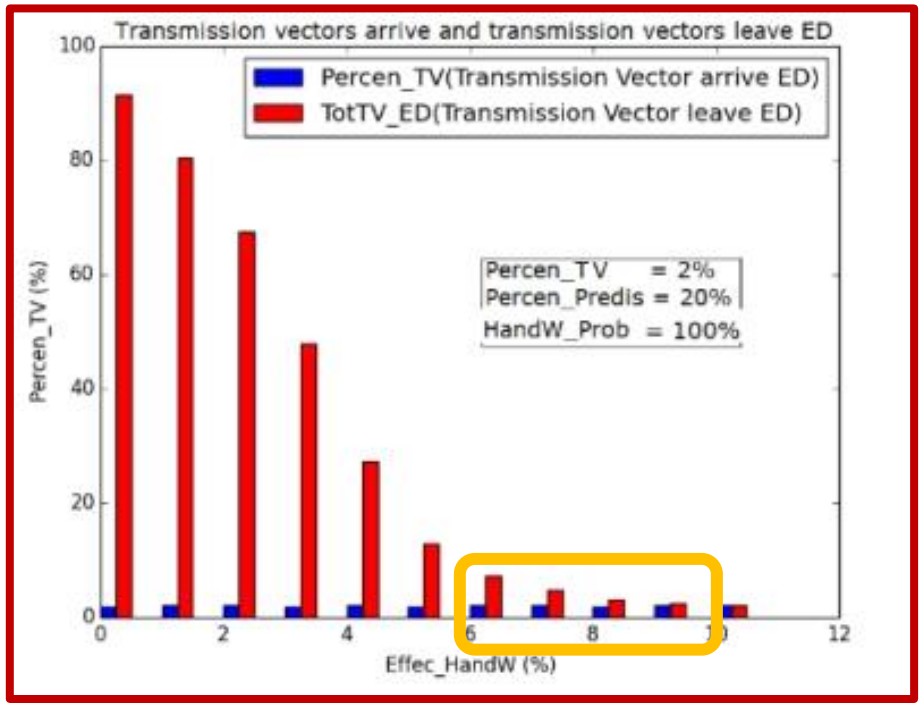
Effec_HandW	0	10	20	30	40	50	60	70	80	90	100
Colon_arrive	222	246	240	252	247	259	241	259	229	255	265
Infec_arrive	242	244	248	220	235	207	238	227	228	231	234
NonCol_arrive	23491	23467	23468	23483	23474	23490	23476	23469	23498	23471	23458
TotPat_arrive	23955	23957	23956	23955	23956	23956	23955	23955	23955	23957	23957
Percen_TV(%)	1,94	2,05	2,04	1,97	2,01	1,95	2,00	2,03	1,91	2,03	2,08
Colon_ED	12868	11326	9411	6634	3723	1568	757	379	169	74	0
Infec_ED	8573	7431	6258	4393	2355	1074	513	263	107	40	0
TotTV_ED(%)	91,44	80,34	67,44	48,00	27,38	12,97	7,30	4,71	3,06	2,50	2,08

Simulation: Results Case Study A

Efficiency

Output dates:



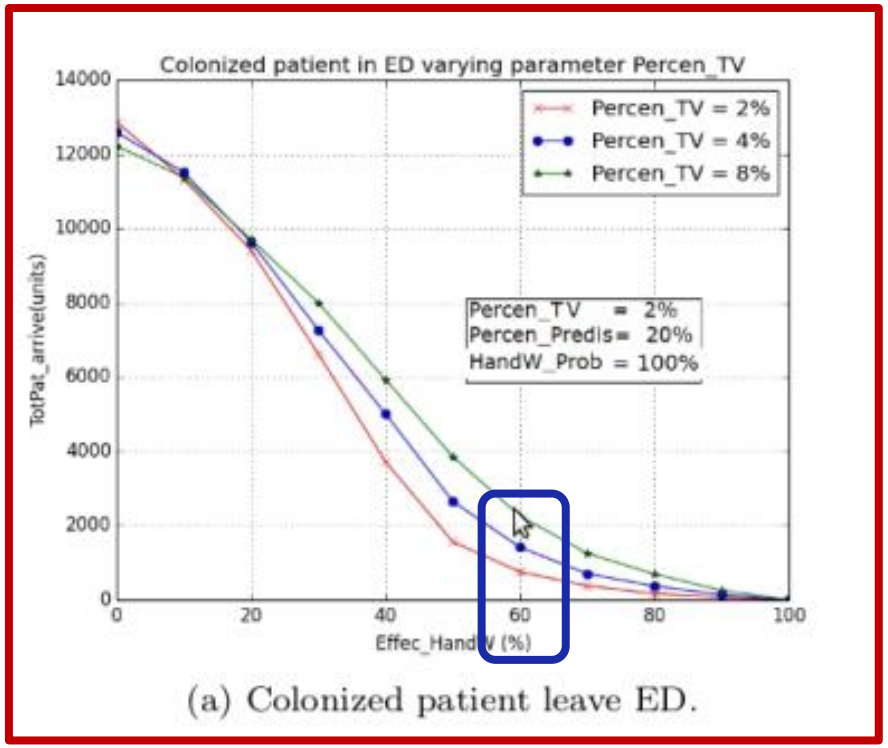


Colonized and Infected Patients with a hand wash (HW) accomplishment of 100% and differents values of effectiveness.

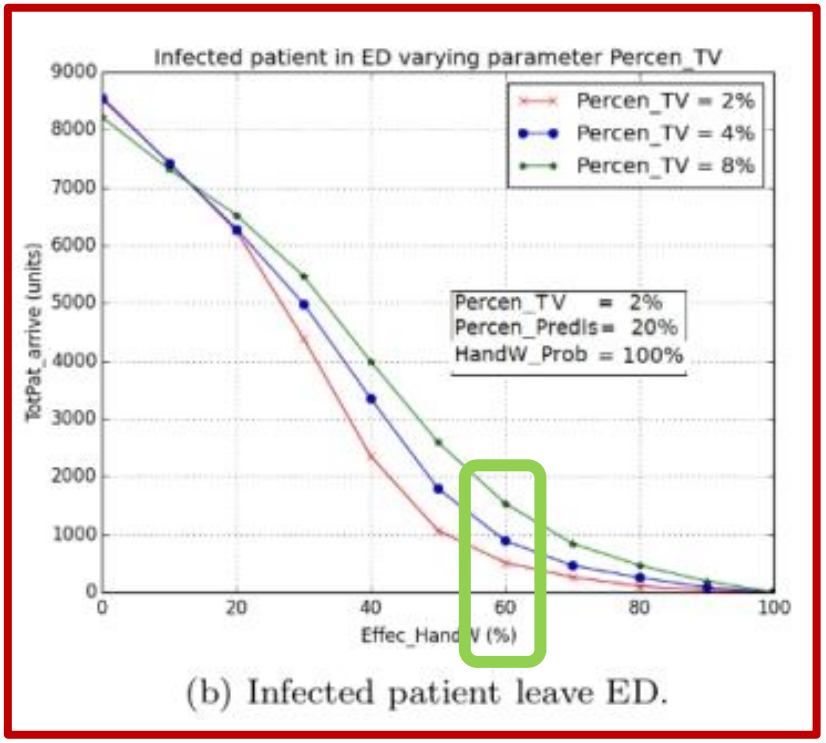
Simulation: Resultas Case Study A

Outputs dates:

Sensitiviy to "Percent_TV"
(Transmission Vector)



(a) Colonized patient leave ED.



(b) Infected patient leave ED.

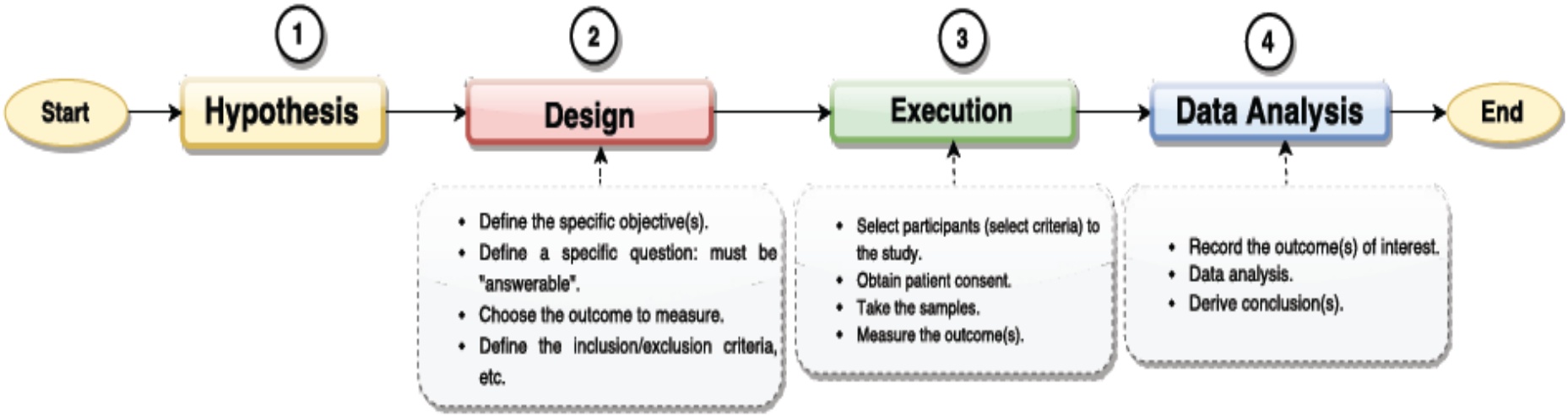
Influence of hand wash (HW) effectiveness in the number of colonized and infected patient with MRSA during the attention process at ED.

Those that Simulation of Health Services gives us

- "Visiting the future" and taking decisions
- Simulation as a source of data
- Impossible/forbidden experiments
- ✓ **Virtual Clinical Trials**

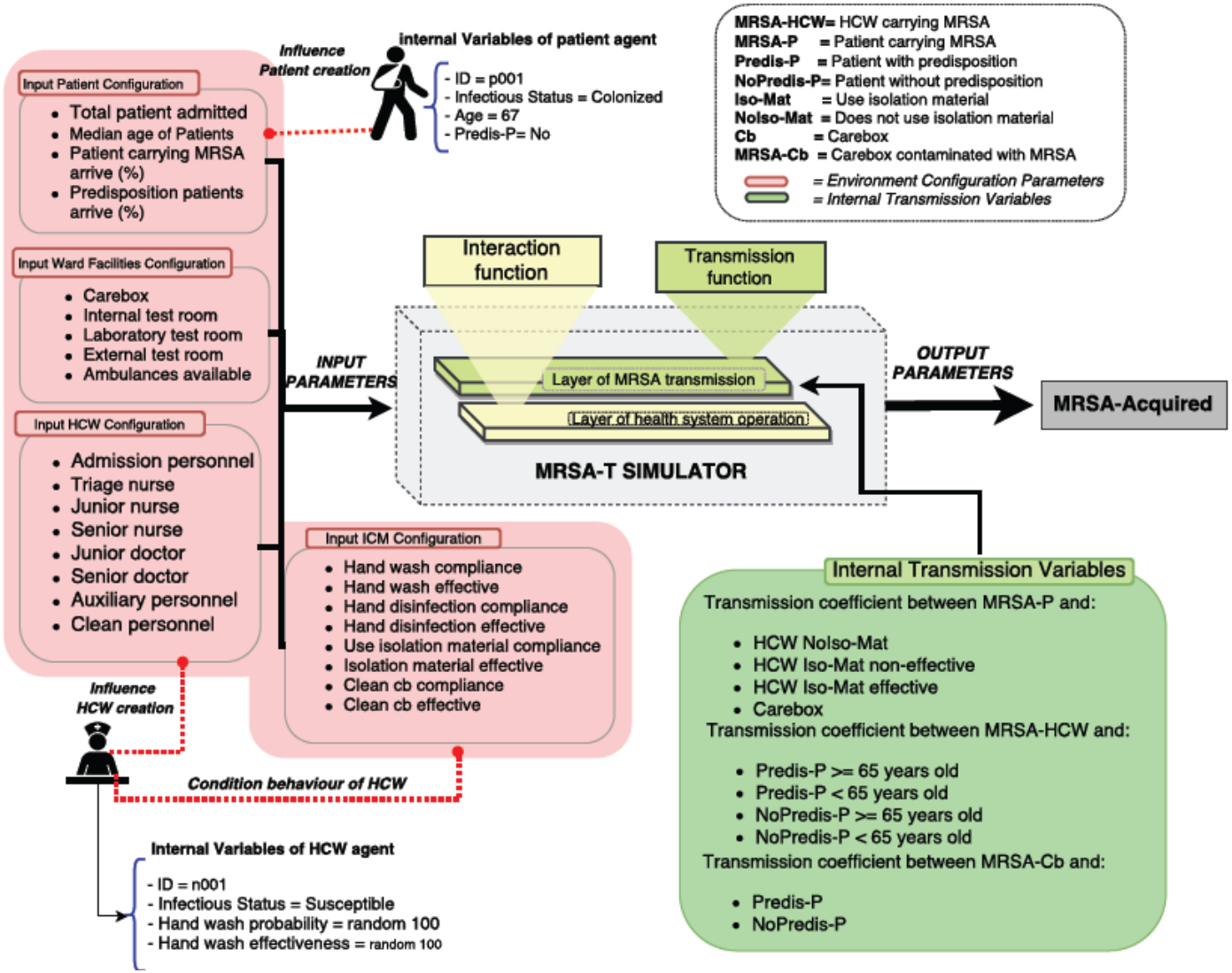
Clinical trial design

Clinical Trial: Any research study that prospectively assigns **human participants** or **groups of humans** to one or more health-related **interventions** to evaluate the **effects on health** outcomes. Interventions include, but are not restricted to drugs, cells and other biological products, surgical procedures, radiologic procedures, devices, behavioural treatments, process-of-care changes, preventive care, etc."



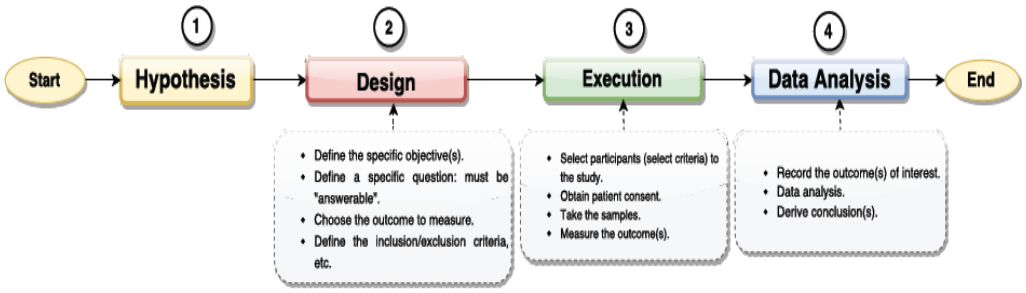
Flow of Clinical Trial Design and Execution Process

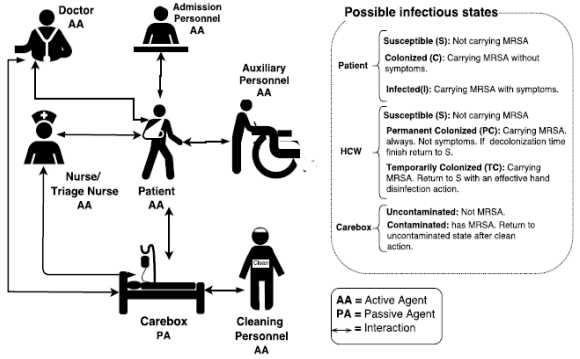
Simulator: Virtual Clinical Trial design



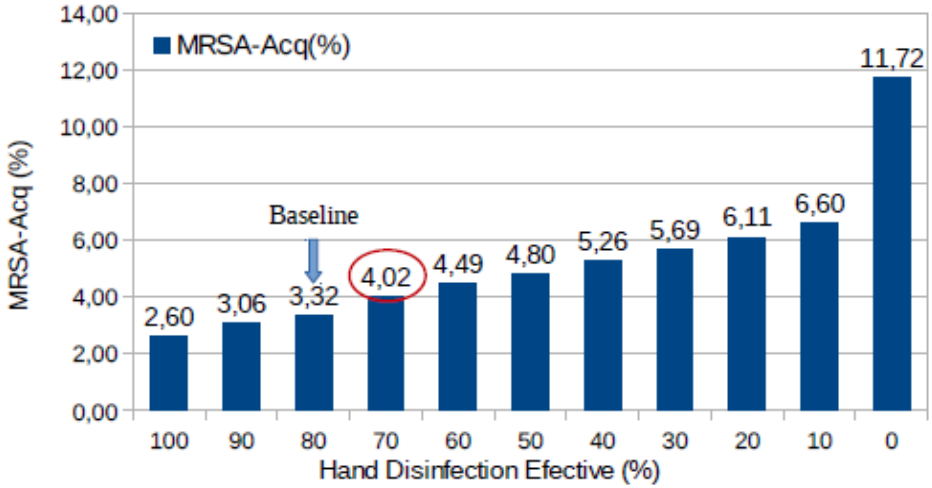
MRSA-T-Simulator: Environment Configuration Parameters and Internal Transmission Variables

Virtual Clinical Trial (VCT) Results





Contacts between agents involve in transmission process.



(a)

VCT	HW-Effect	Patients included VCT (>48h)	Patients MRSA-Acq	Patients MRSA-Acq(%)
1	100	1277,23	29,23	2,60
2	90	1274,27	34,38	3,06
3	80	1269,53	37,02	3,32
4	70	1277,50	45,27	4,02
5	60	1274,64	50,28	4,49
6	50	1269,91	53,55	4,80
7	40	1276,09	59,04	5,26
8	30	1272,83	63,67	5,69
9	20	1275,91	68,48	6,11
10	10	1271,87	73,86	6,60
11	0	1275,27	131,31	11,72

Baseline

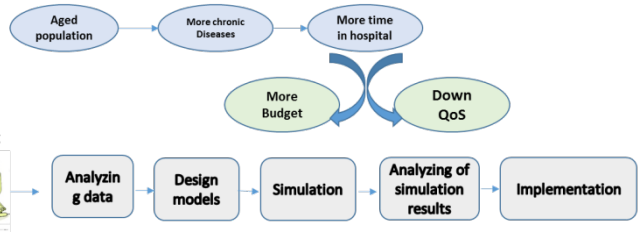
(b)

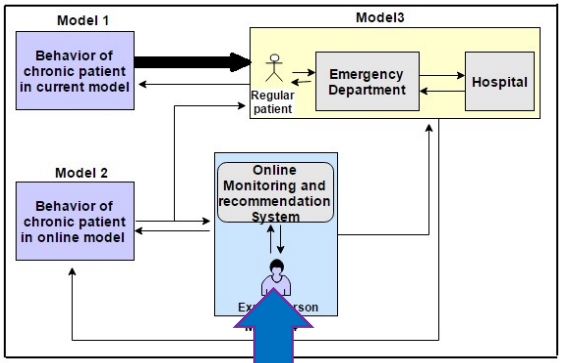
(a) Percentages of MRSA-Acq(%) for 11 VCTs. (b) Output data for 11 VCTs based on Control Case. A decrement of Hand Wash Effective variable is apply in each VCT.

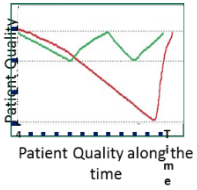
Where are we going? The Future

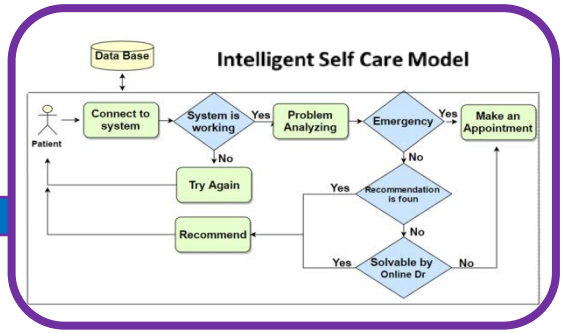
Chronic Diseases-eHealth

- By ageing population we will have an increase in chronic conditions
- Increasing ageing population increase demand of health Care system or budget

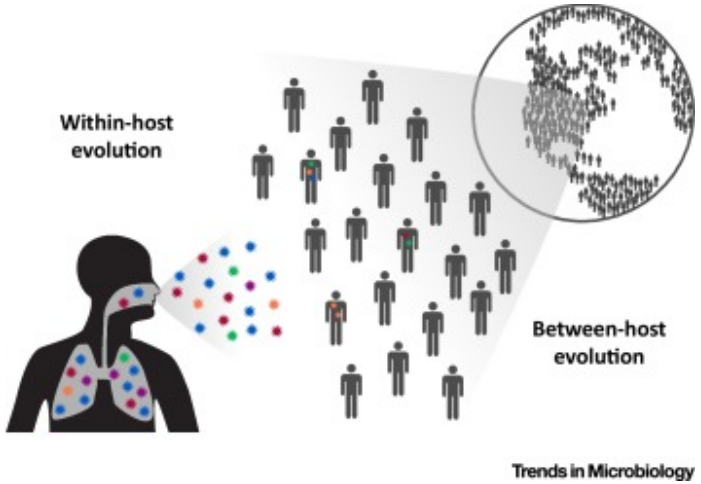








Flu Propagation in ED



Conclusions

Simulation:

- Data
- Information
- Knowledge

Based on **MODELS**

(**Glass Box** vs Black Box)

The Eleventh International Conference on Advances in System Simulation

SIMUL 2019

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Thank you very much for your attention

Universitat Autònoma de Barcelona

HPC4EAS Research Group

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