Modeling and Simulation for Healthcare Operations Management using High Performance Computing and Agent-Based Model

for Ph.D. program in "Informática, RD 99/2011"

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Motivation

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-> Predict system performance for a specific configuration, cost and benefit for a proposed change.

-> Explain factors influencing performance, how the prediction is made and why it performs like this.

-> Optimize changes to the system with constrain like budget.

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2. A platform to study emergency department related problems:

-> Bacteria propagation. (e.g., MRSA infection)

-> Study disordered system behavior based on integration of first-principles model and data-driven model (real operation data).

Outline

- Introduction
- The general emergency department model
- Automatic model parameters calibration under data scarcity
- Decision support examples
- Conclusion, future work & related publications

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Key points:

- It is the main entrance to healthcare system, the Efficiency and Quality of Service (QoS) in ED has big influence to the whole healthcare system.
- Patients arrive the ED without prior appointment, some of them with unstable conditions and must be treated quickly!
- Some EDs are overcrowding and work with limited budget.
- ED is a complex & critical system with many constraints!

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Emergent Property: an observation about a system that we might not anticipate from the separate study of its individual components (Holland, 1998; Strogatz, 2003).

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 (Roetzheim). This characteristic makes the output of a system difficult to understand and predict.

What is an agent-based model ?

An agent-based model is one of a class of computational models for simulating the **actions** and **interactions** of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole.

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Key points:

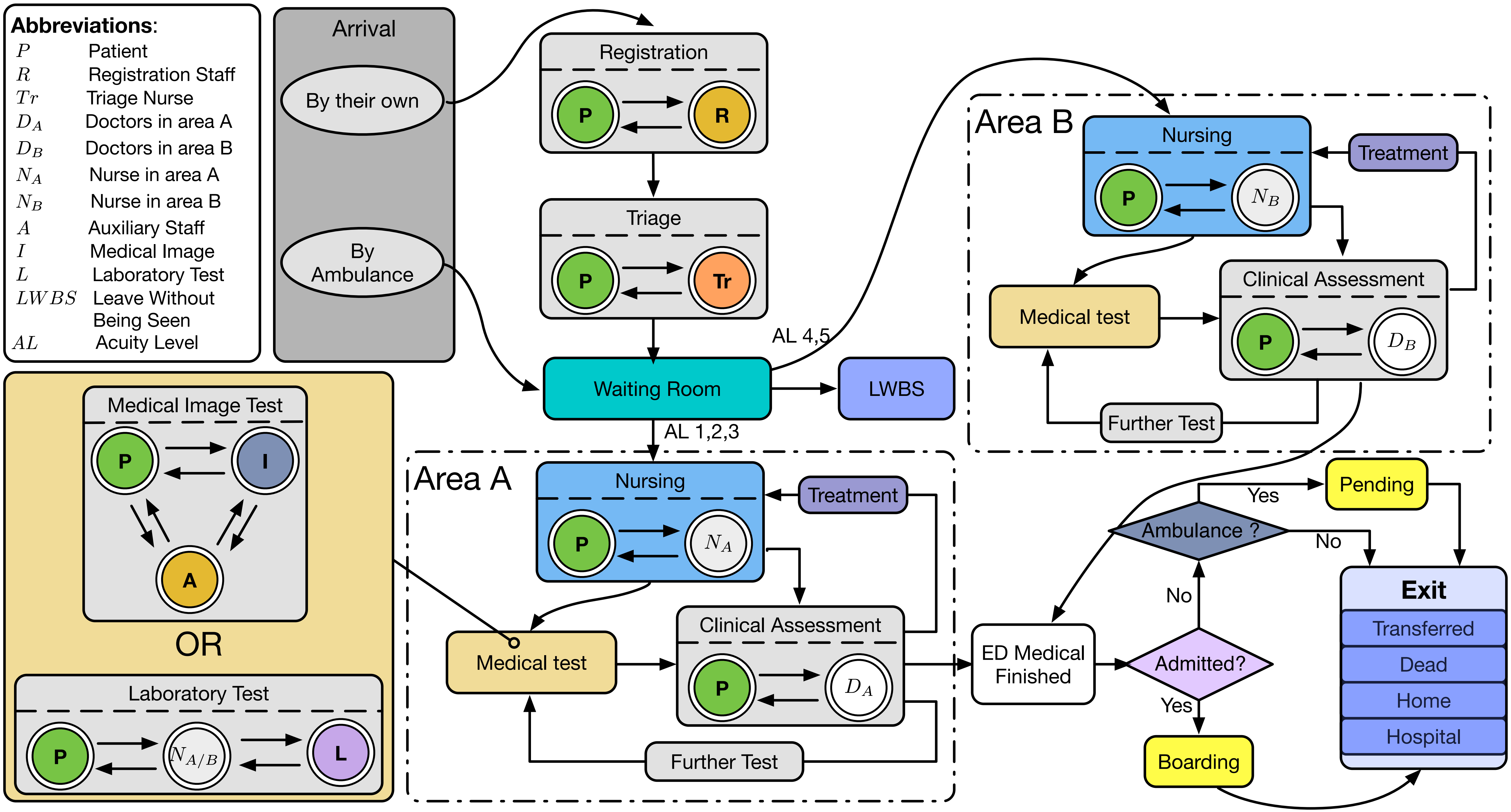
- It can be used to capture emergent phenomena, and it gives **insights** into causes of emergent phenomena.
- In which, systems are described in a "**natural**" way which leads to a wider acceptance of the modeling approach.
- It is **flexible** and can easily be adapted to new constraints (for testing strategy).
- *Computation expensive.*
- *Calibration, Verification and Validation (expensive to play).*

- Introduction
- ***The general emergency department model***
- Automatic model parameters calibration under data scarcity
- Case studies
- Conclusion, future work & related publications

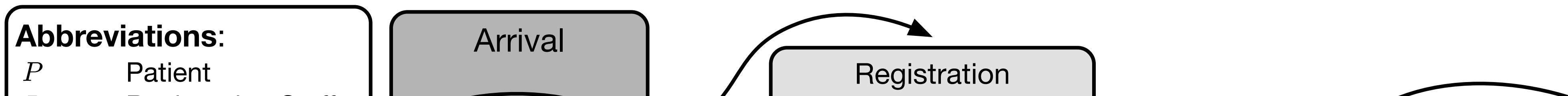
Outline - the model

- The conceptual model. *(How does the target system work.)*
- Agents' model. *(individual behavior rules.)*
- Interaction model.
- Design of experiment and efficient execution

Conceptual model - how does the system work?



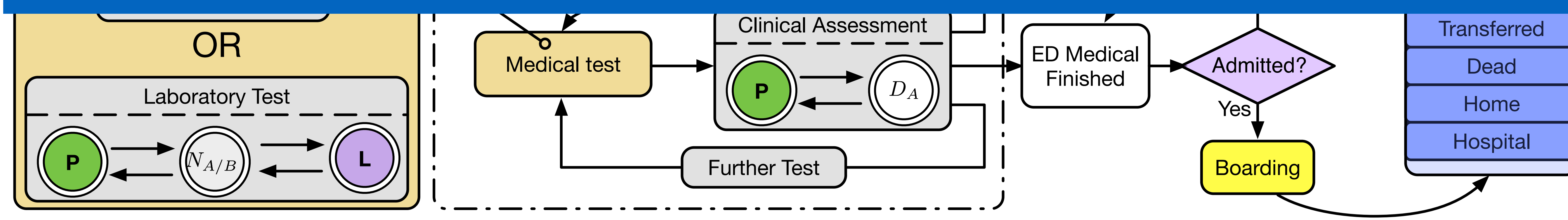
Conceptual model - how does the system work?



Note:

§ Every patient who comes through the door is an unknown, with a condition that unfolds over time in a functionally **non-deterministic** way. Theoretically speaking, no two paths through this “system” are the same for any two patients.

§ It may vary in different EDs but the underlying methodology is the same, i.e., mimic individual's (AKA: agent, system-component) behavior and simulate their interaction.



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Behavior rules of patients

IF	THEN
notified by IS (before entering treatment area).	go to the corresponding place in the notification.
no requests from IS (before entering treatment area).	keep staying in waiting room.
no interaction requested by healthcare staff (nurse, doctor or auxiliary).	keep staying in carebox (for patients in area A).
no requests from IS or healthcare staff.	keep staying in waiting room (for patients in area B).
notified by IS (in area B).	go to diagnosis room or medical image test-room as indicated in the notification.
needs additional help.	ask nurse through IS (the IS will notify the corresponding nurse).

Behavior rules of doctors

IF	THEN
time to work.	interact with doctor in previous shift, take over patients from them.
no task assigned by IS (task queue is empty).	stay in their office (IDLE).
IS notifies a new patients in carebox i (in area A) / A new patient comes into office (in area B).	move to carebox i (in area A), perform first-interaction, make treatment plan.
IS notifies: the test report for one of the patients in set D_i^P is ready to review.	review medical test report, walk to the carebox (in area A) if necessary, and make follow-up treatment plan (do more test, drug therapy, discharge or admit to hospital).
scheduled drug therapy time of any patient in set D_i^P is up.	walk to the carebox (in area A), check effect of drug therapy, and make follow-up treatment plan.
shifting of duty time is up.	accomplish work at hand, interact with doctors in following shift, hand over all the patients in D_i^P.

* rules specified with *in area* A means doctors in area A, otherwise applies to area A and B.

UAB

Behavior rules of nurses

IF	THEN
time to work.	interact with nurse in previous shift, take over patients from them.
no task assigned by IS (task queue is empty).	stay in the nurse room.
doctor assigned laboratory test to one of the patients in set N_i^P.	walk to the patient (to carebox N_i^{CB} in area A), taking sample from patient.
drug therapy assigned to one of the patients in set N_i^P by doctor.	go to the pharmacy, take pill and then walk to the place of patient for treatment.
IS notifies an additional-help call from patient in set N_i^P.	go to the patient (to carebox N_i^{CB} in area A).
Periodic checking time is up.	Check every patient's body condition in set N_i^P.
doctor discharged one patient in set N_i^P.	help patient leaving ED.
shifting of duty time is up.	accomplish task at hand, interact with nurses in following shift, hand over all the patients in set N_i^P.

* rules specified with *in area* A means nurses in area A, otherwise applies to area A and B.

Behavior rules of others

The registration staff / triage nurse;
The medical image test-room;
The laboratory test-room;
The auxiliary technician
… …

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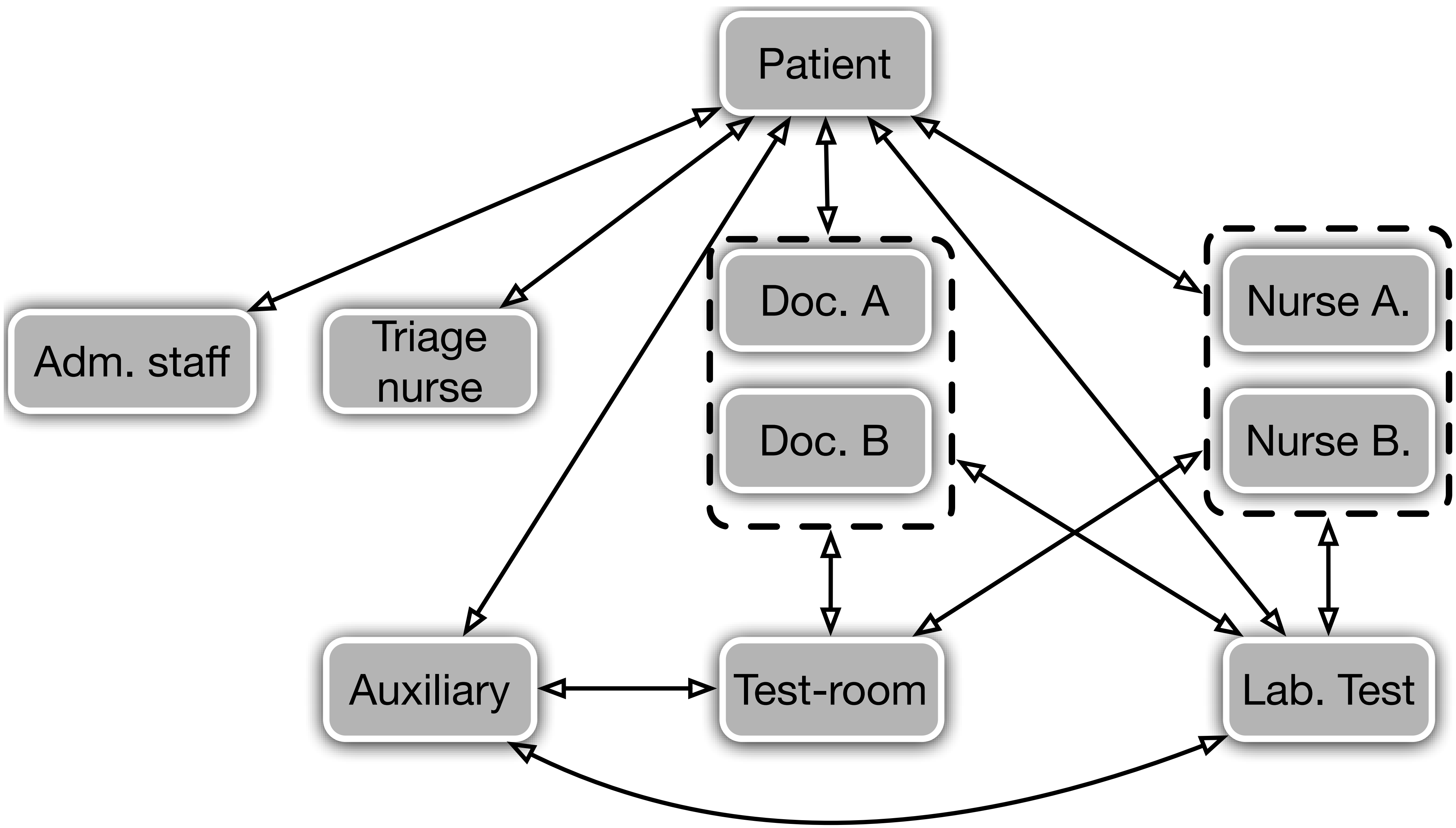
Scheduler: Information System



Service time / Interaction time

$$T_{st} = Exp(\lambda_{st}) + t_{move}, \qquad \lambda_{st} = \gamma_n \cdot f(s, sp, al)$$

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Where, T_{st} is the service time for one interaction, s denotes the type of service (purpose of interaction), sp is the experience of the service provider (doctor, nurse, test-room), say, junior or senior; al represents the acuity level of patients; t_{move} is the time takes on movement which depends on the location of the patient's carebox. t_{move} is set as zero in area B.

The γn represents the proportionality coefficient for the first meeting with patient and follow-ups (e.g., 1.0 for first meeting and 0.7 for follow-ups).

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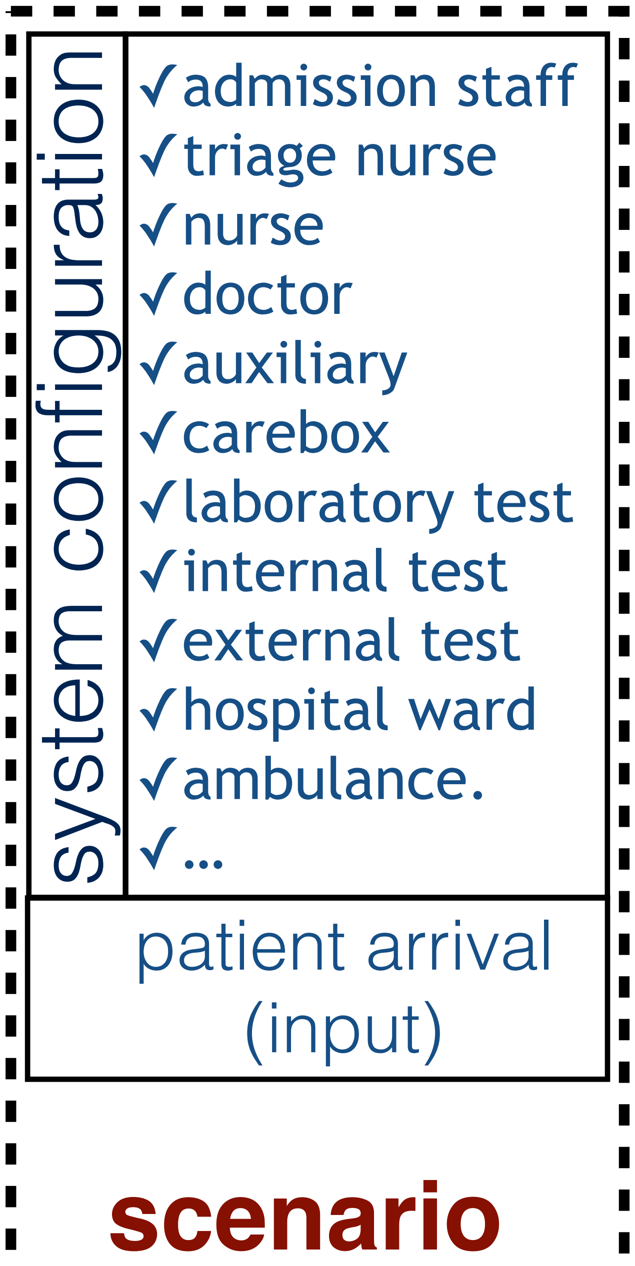
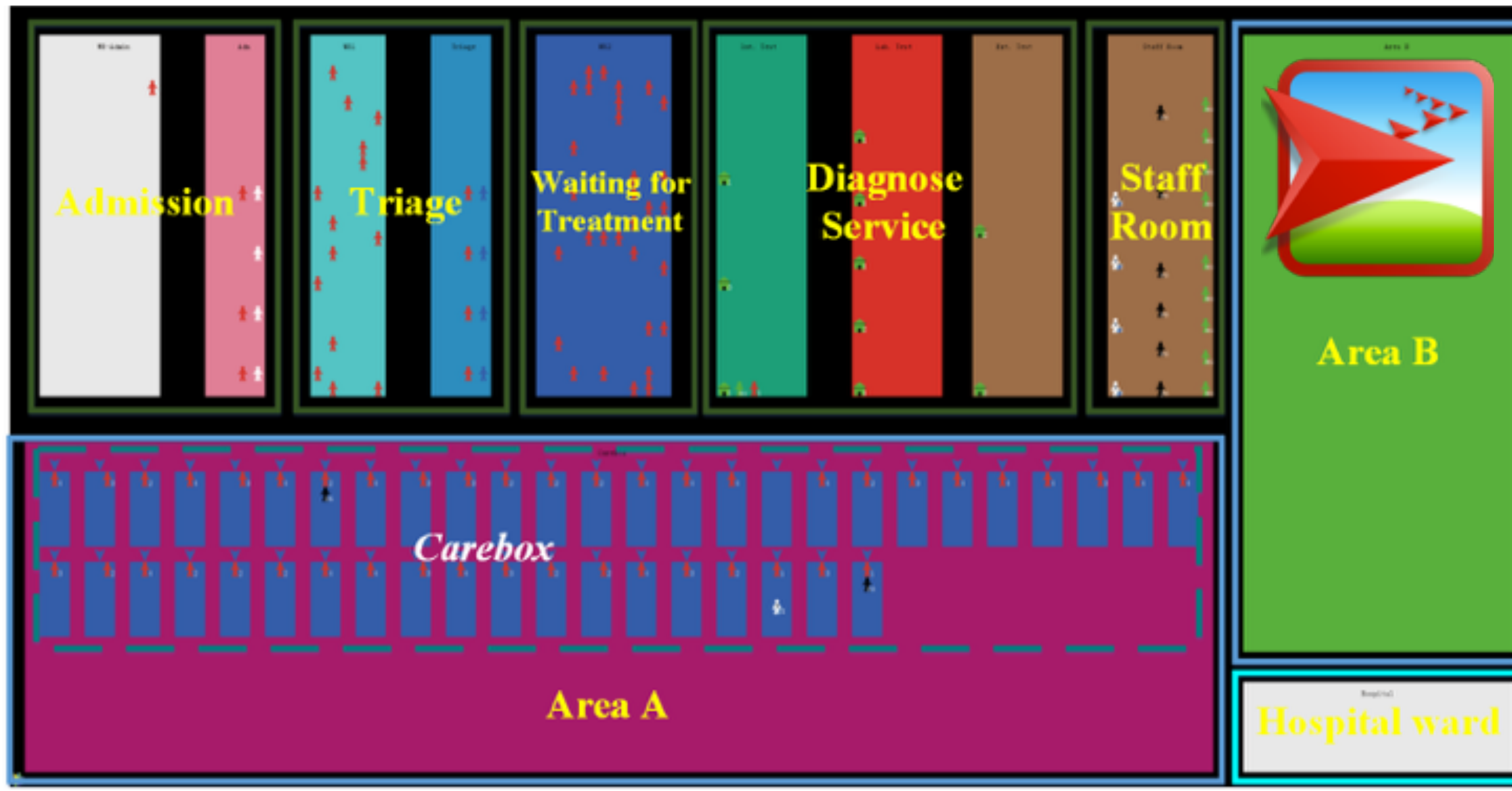


Design of experiments

system configuration
- ✓admission staff
- ✓triage nurse
- ✓nurse
- ✓doctor
- ✓auxiliary
- ✓carebox
- ✓laboratory test
- ✓internal test
- ✓external test
- ✓hospital ward
- ✓ambulance.
- ✓...

patient arrival (input)

scenario



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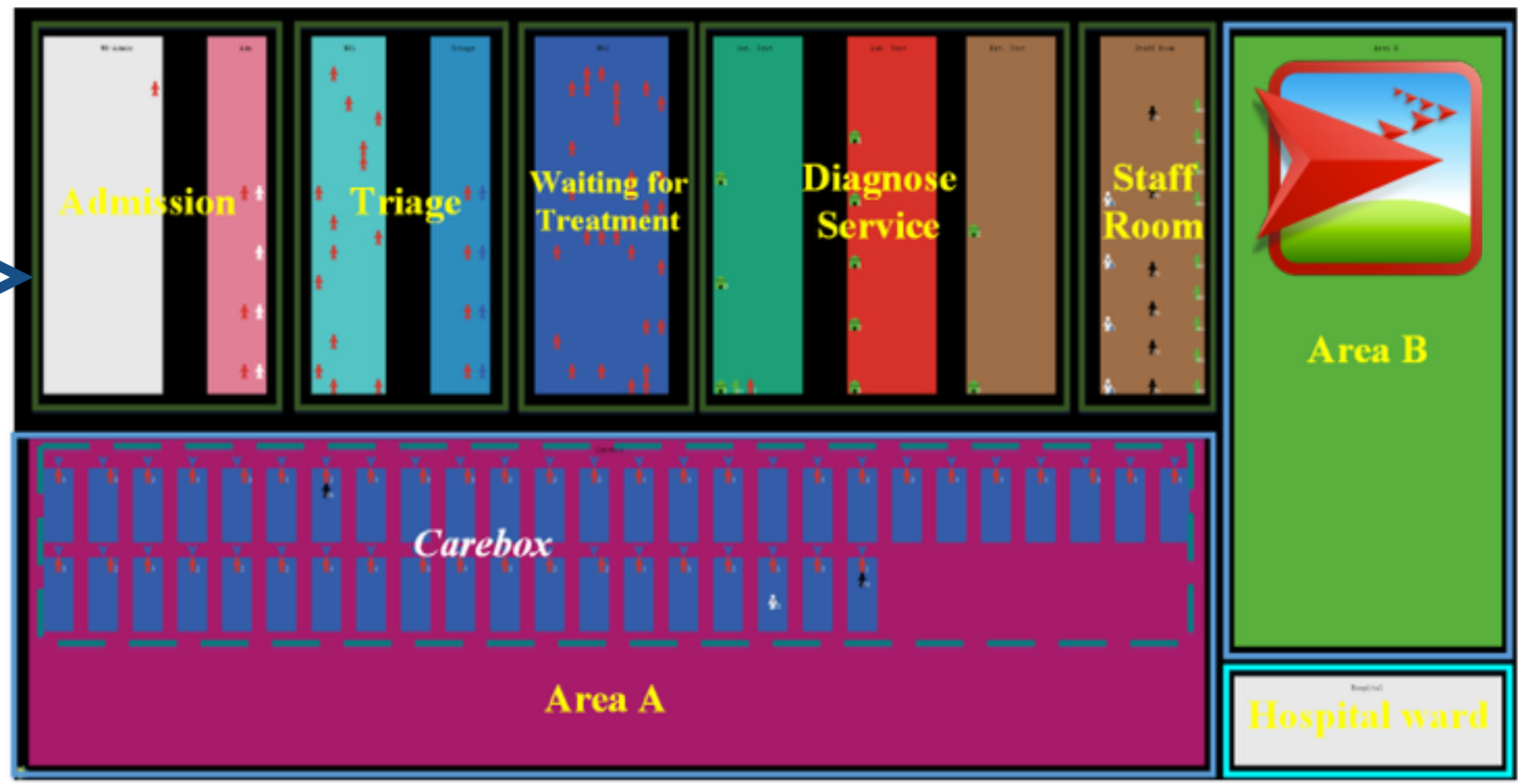

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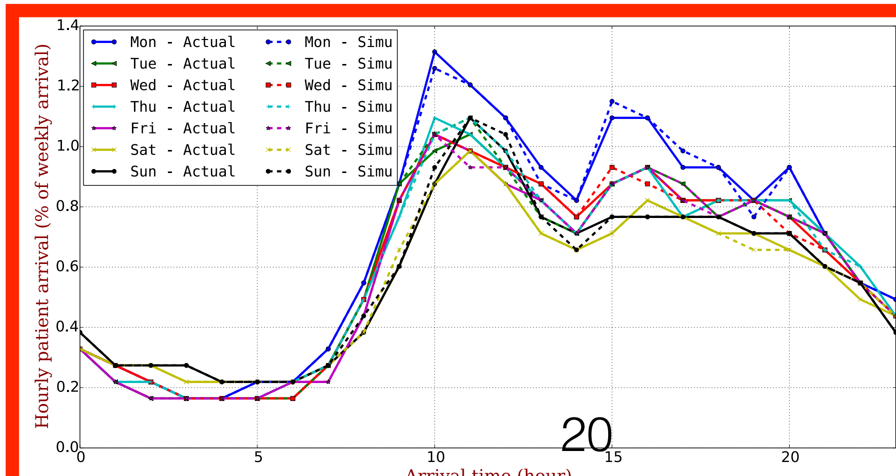
patient arrival (input)

scenario

Resource	Capacity (#)		Avg. Attention Time (AT, minutes)		AT Distributic
	day	night	first interaction	follow-up	
junior admission staff	3	2	5		Gamma
senior admission staff	2	0	3		Gamma
junior triage nurse	3	1	8		Gamma
senior triage nurse	2	1	6		Gamma
junior doctor in area A	2		20	15	exponential
senior doctor in area A	4		15	13	exponential
junior nurse in area A	5		25	18	exponential
senior nurse in area A	5		20	14	exponential
junior doctor in area B	2		8	7	exponential
senior doctor in area B	5		6	5	exponential
junior nurse in area B	4		11	7	exponential
senior nurse in area B	4		7	5	exponential
medical imaging test room	5	2	45		Beta
laboratory test place	4	2	30		Beta
carebox in area A	50		-		-
chair in area B	60		-		-
auxiliary nursing staff	3		15		exponential

Should execute many times for each scenario

Statistical Model



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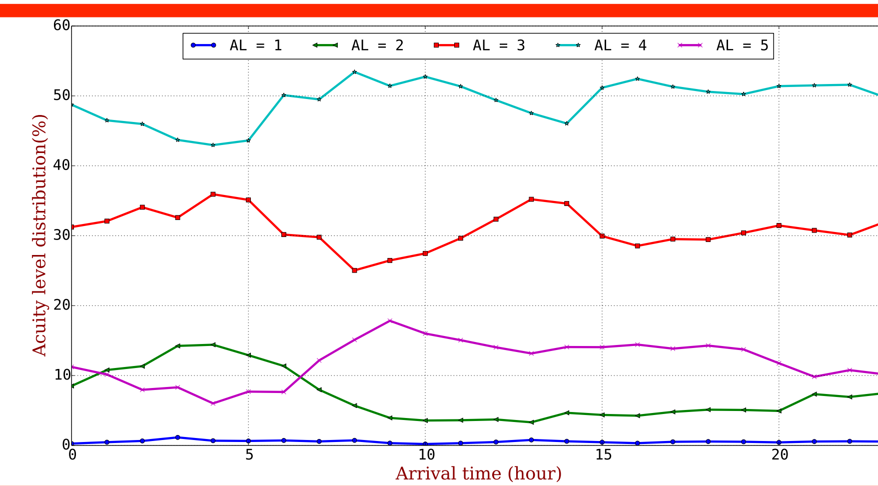
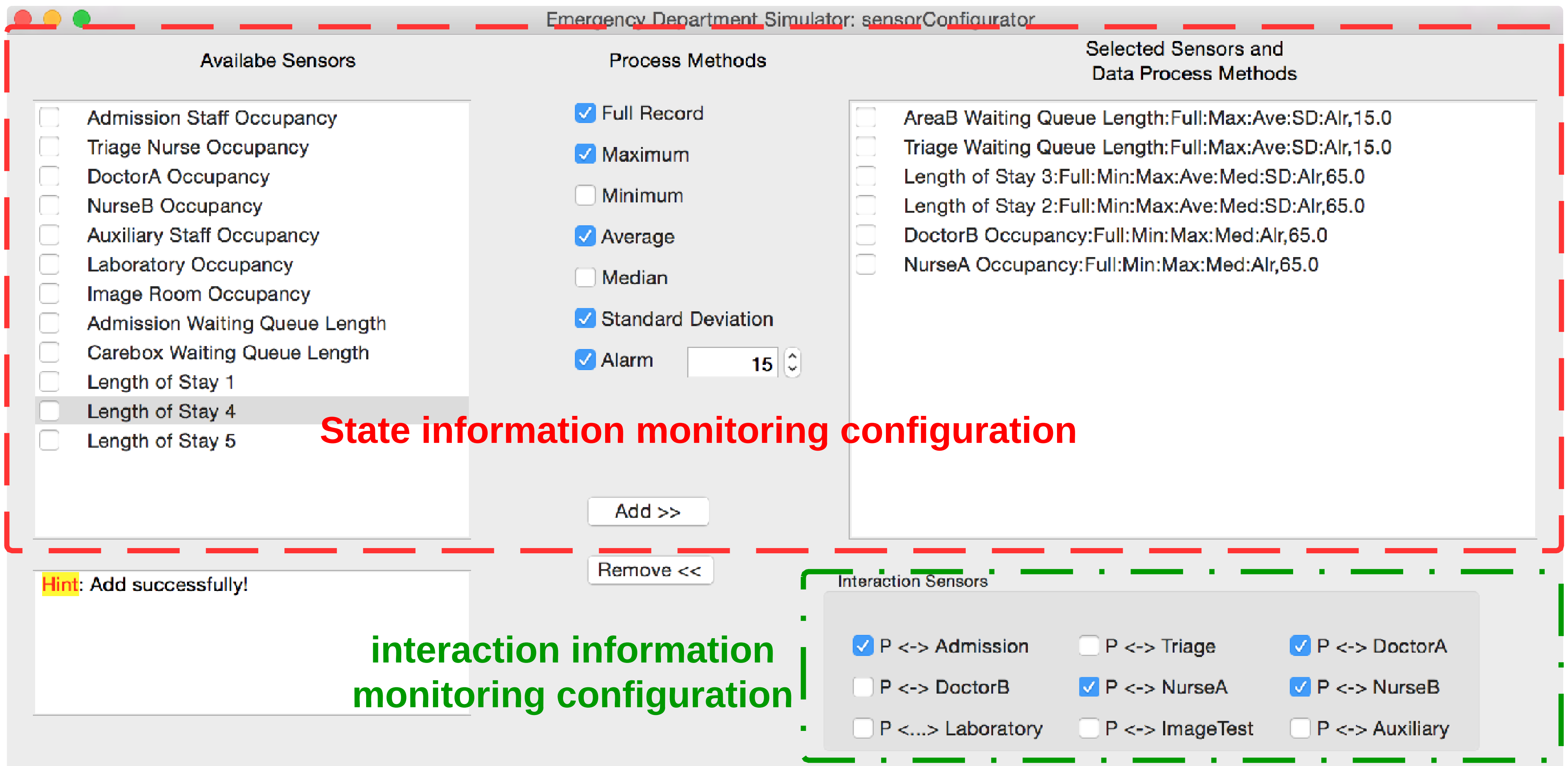


Customize simulator - Simulation data collection



It is like: we could put a device (*sensor*) on *each* of the individuals to monitor their *detailed activities*. **sensors are customizable and have process capability.**

Extract performance indicators from interactions data

1	who	what	when(minute)	where	why	how long(second)
86179	(doctorb 76) and (patient 16279)	first-visit	70446	doctorB's room	default	1200
86180	(doctorb 74) and (patient 16283)	first-visit	70447	doctorB's room	default	900
86181	(nursea 80) and (patient 16158)	go-home	70447.5	carebox	default	150
86182	(doctorb 75) and (patient 16277)	first-visit	70448	doctorB's room	default	210
86183	(doctorb 78) and (patient 16222)	treatment-finished	70449	doctorB's room	default	1320
86184	(doctora 69) and (patient 16211)	test-result-review	70449.5	carebox	default	330
86185	(doctorb 73) and (patient 16281)	first-visit	70449.5	doctorB's room	default	1290
86186	(admission 1) and (patient 16285)	admission	70451.5	admission desk	default	300
86187	(doctora 67) and (patient 16199)	test-result-review	70451.5	carebox	default	120
86188	(nursea 80) and (patient 16199)	laboratory test	70453.5	carebox	default	1080
86189	(nursea 84) and (patient 16211)	go-hospital	70455	carebox	default	1290
86190	(doctora 69) and (patient 16262)	test-result-review	70455.5	carebox	default	450
86191	(doctorb 77) and (patient 16154)	treatment-finished	70455.5	doctorB's room	default	510
86192	(doctora 66) and (patient 16033)	test-result-review	70456.5	carebox	default	300
86193	(doctorb 72) and (patient 16247)	test-result-review	70457	doctorB's room	default	360
86194	(admission 2) and (patient 16288)	admission	70460	admission desk	default	240
86195	(doctora 71) and (patient 16236)	treatment-finished	70462	carebox	default	390
86196	(doctorb 74) and (patient 16180)	test-result-review	70462.5	doctorB's room	default	360
86197	(doctora 70) and (patient 16284)	first-visit	70464.5	carebox	default	480
86198	(doctorb 72) and (patient 16285)	first-visit	70465.5	doctorB's room	default	300
86199	(doctorb 77) and (patient 16228)	treatment-finished	70465.5	doctorB's room	default	180

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Length of Stay, Occupancy, Length of Waiting, Efficiency, …

Efficiently execute the simulator with HPC

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Challenges:

§1 probabilistic agent model (sample size).

§2 study more scenarios in acceptable time period.

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Solution:

§1 master-worker

§2 Parametric

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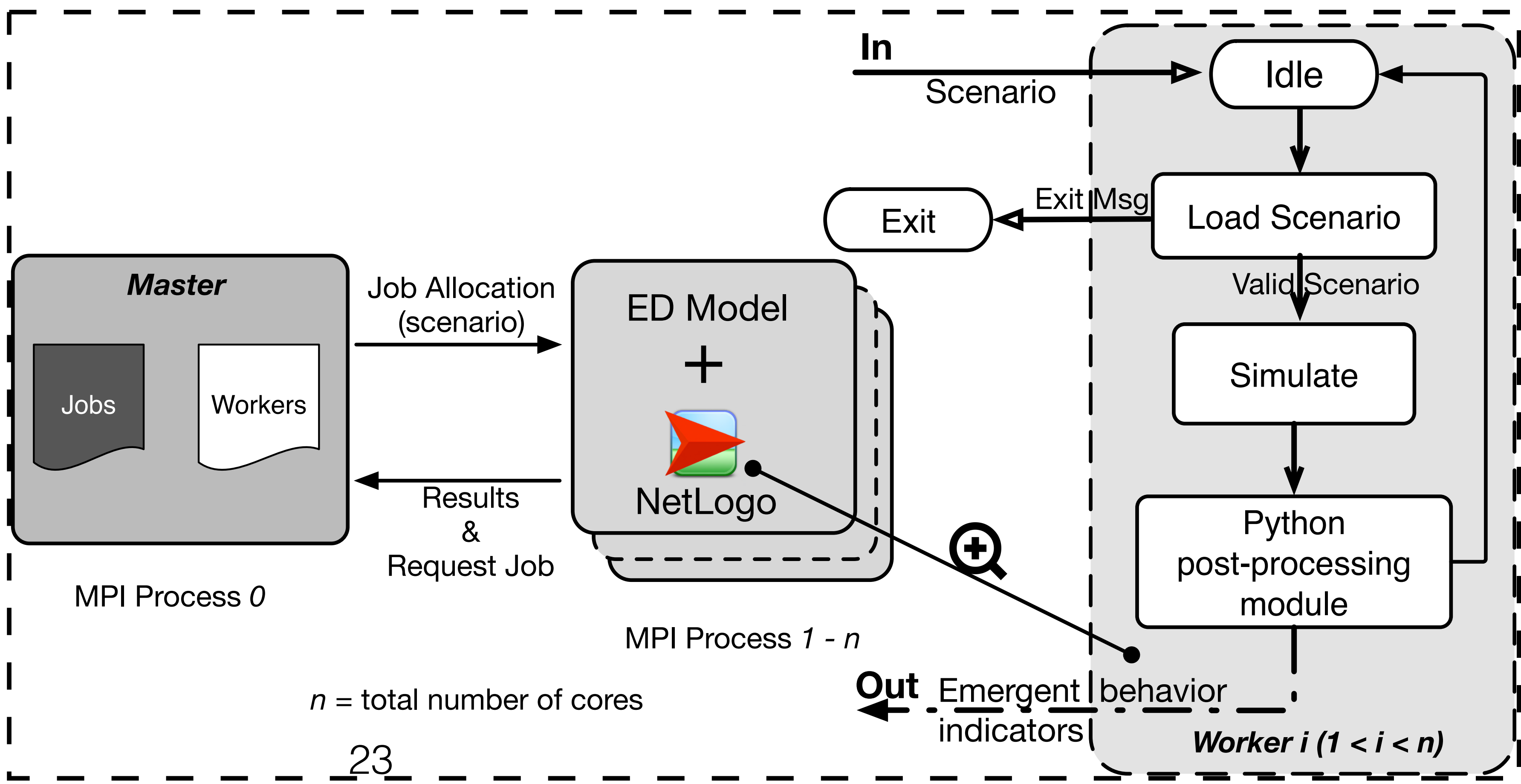

- Introduction
- The general emergency department model
- ***Model parameters calibration under data scarcity***
- Case studies

The problem statement

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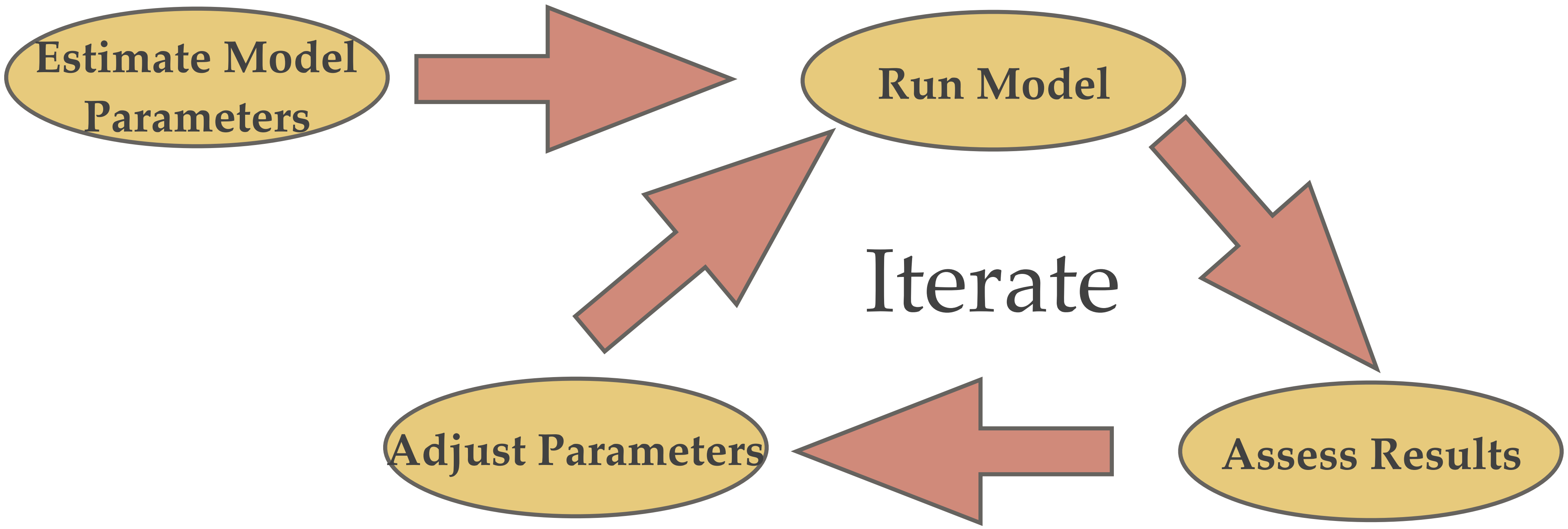
Challenge: Data Scarcity, Out the scope of Information System;
Solution: Form as an optimization problem;
Process: selection of inputs, specifying the objective function, searching, and evaluating the calibration results

Outline - calibration

- Problem statement.
- The fitness function.
- Optimization - search the optimum value.
- Results

The problem statement - process



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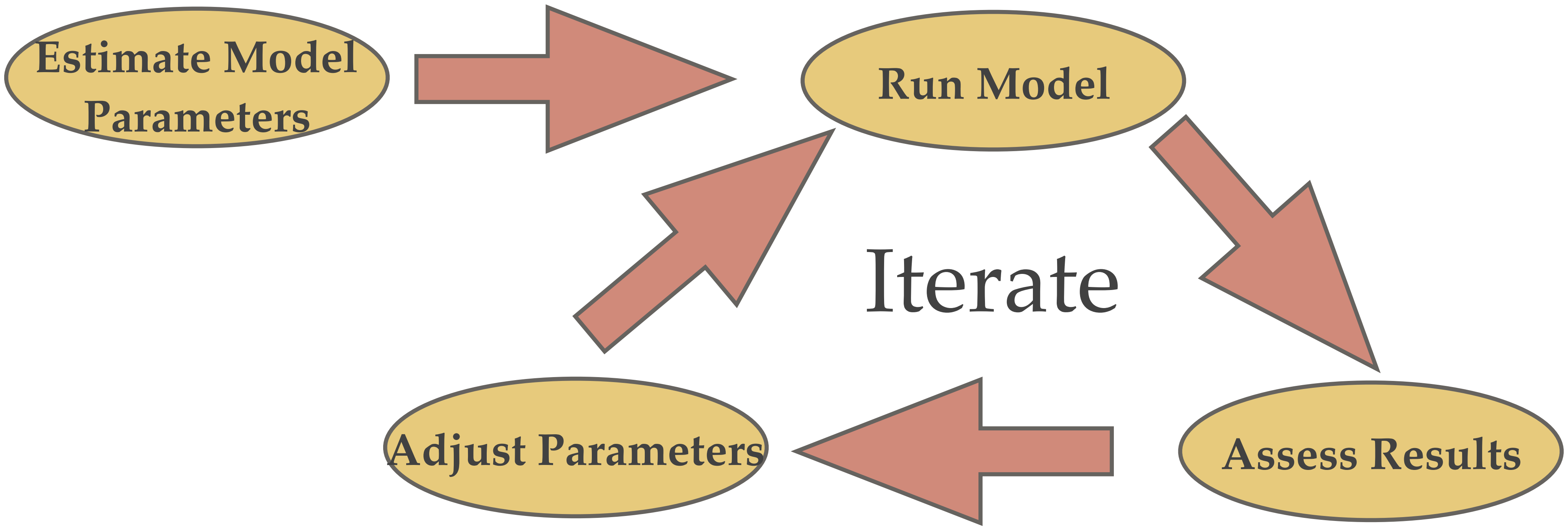


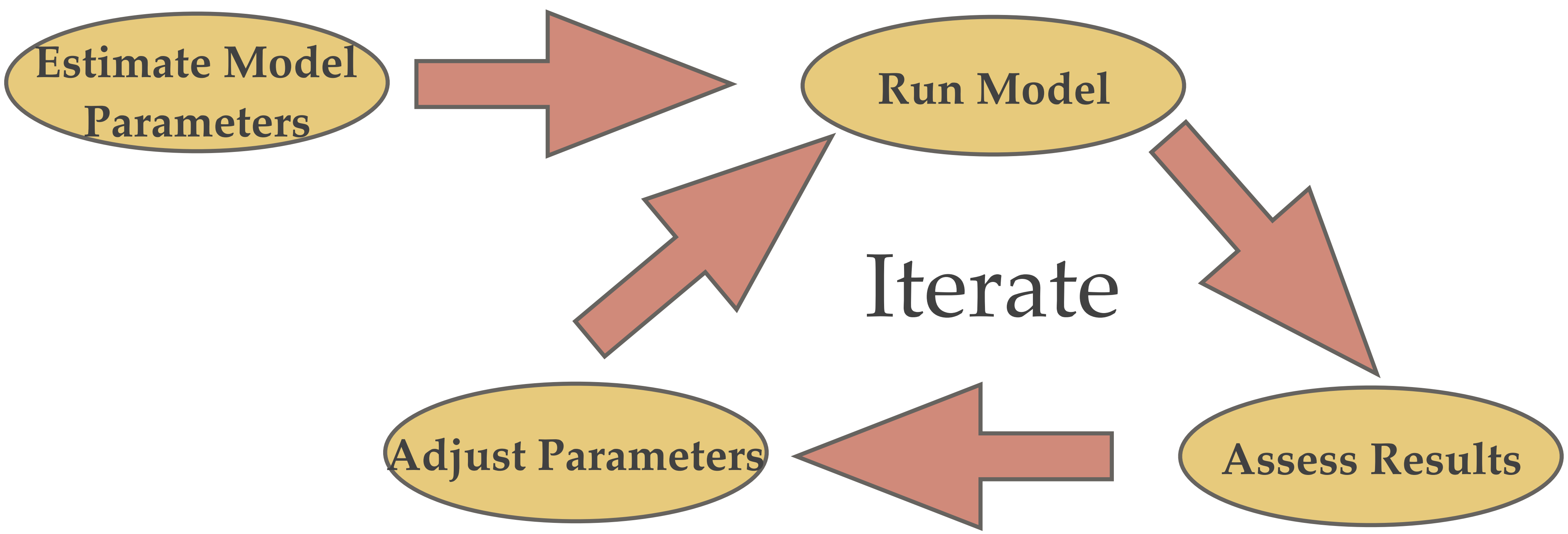
Looks straightforward, but ...

– What **criteria** do we employ to adjust model results?

– How do we go about **adjusting** model inputs?

– How do we know when we have done?

The problem statement - process



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– What **criteria** do we employ to adjust model results?

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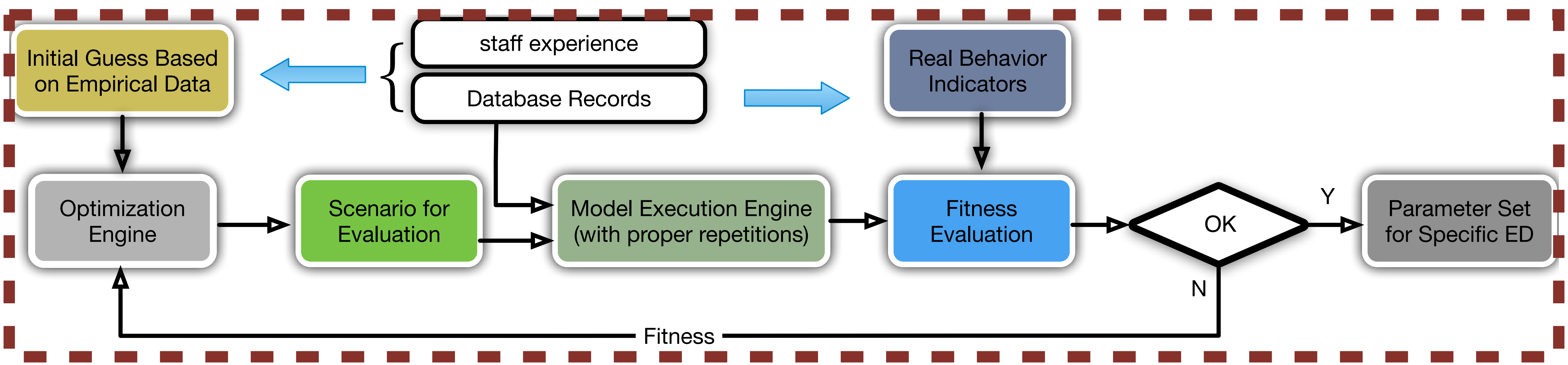
Trial-and-error does not work!

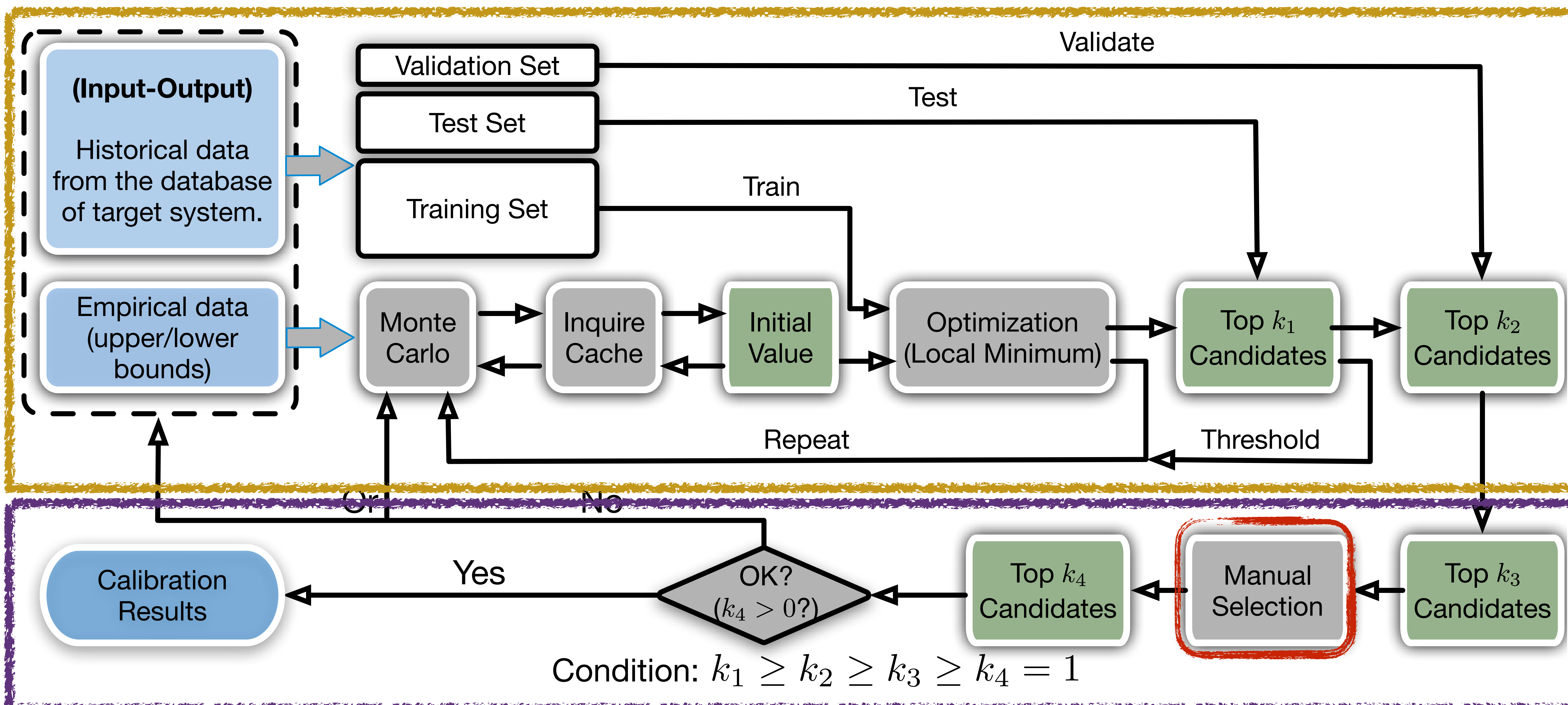
The problem statement - solution

Challenge: Data Scarcity
Reason: Out the scope of Information System
Solution: Formed as an optimization problem

$$Minimize \quad f_{fitness}(p_1, p_2, \cdots, p_n) = L(actual, simulation)$$
$$Subject \quad to:$$
$$p_1, p_2, \cdots, p_n \quad make \quad sense \quad in \quad real \quad situation$$

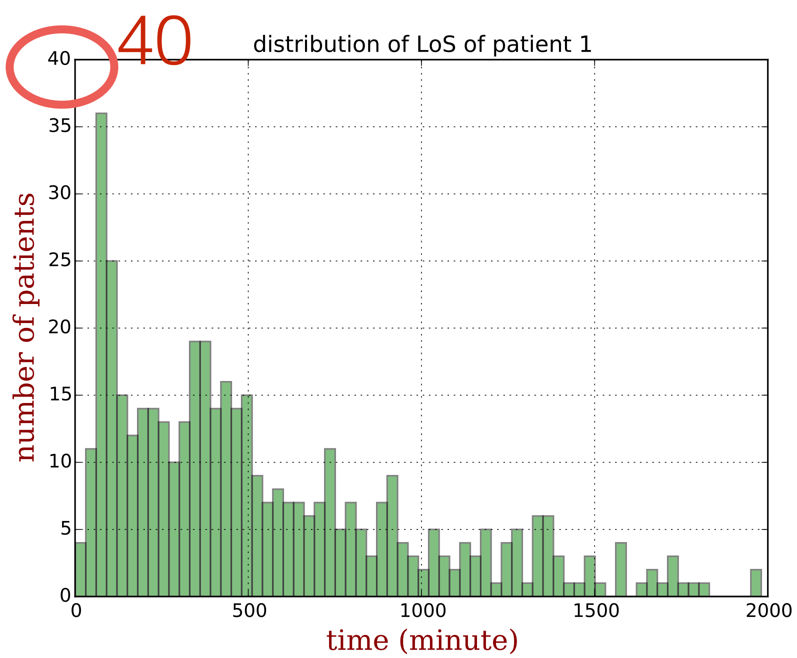


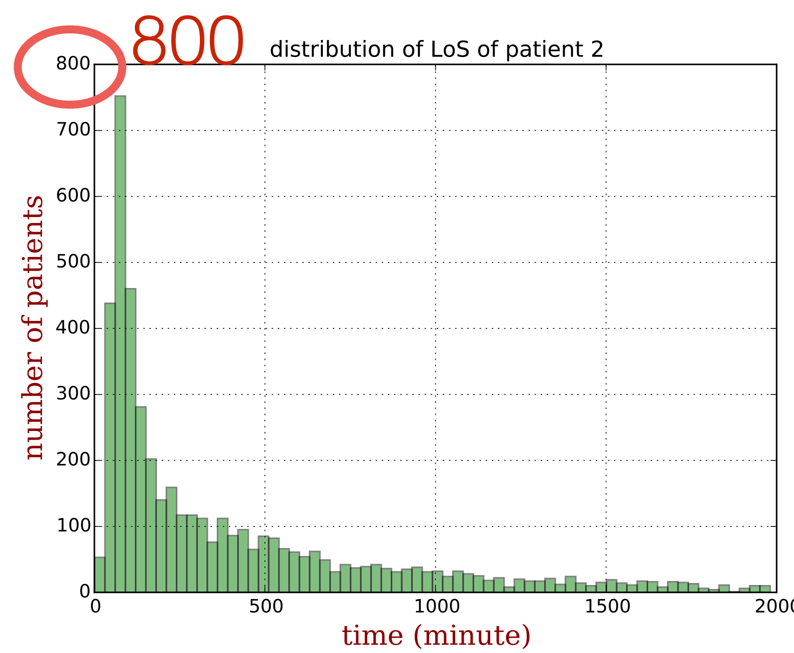
The solution - detailed steps

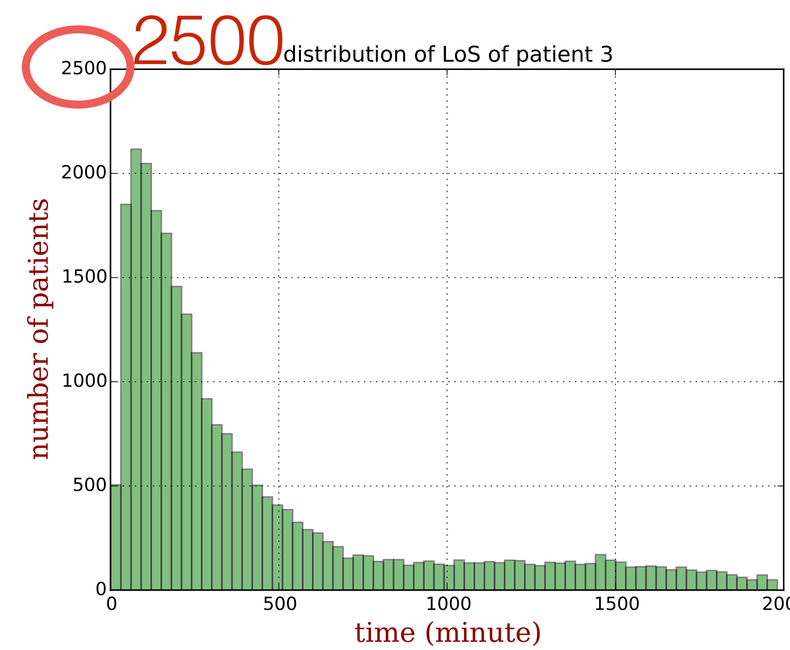


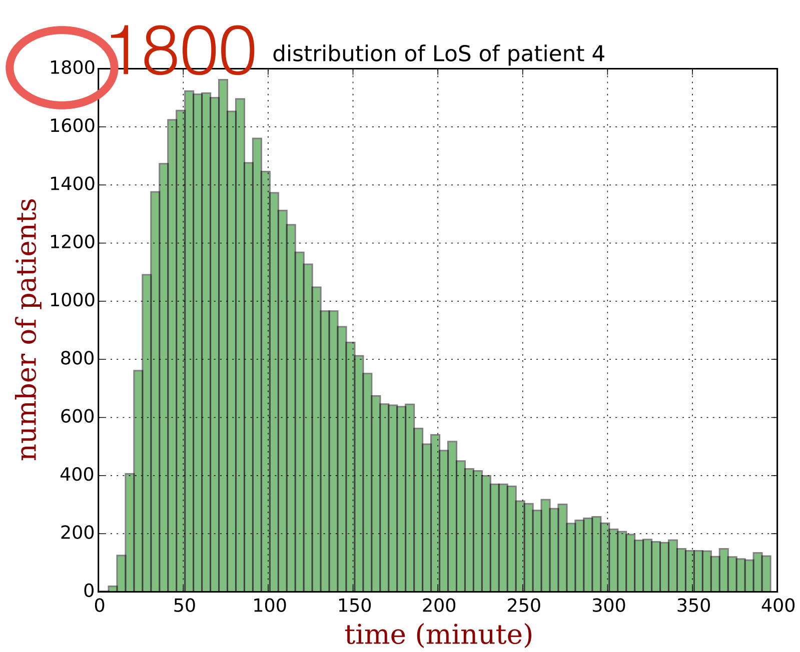
The 1st issue: results assessment

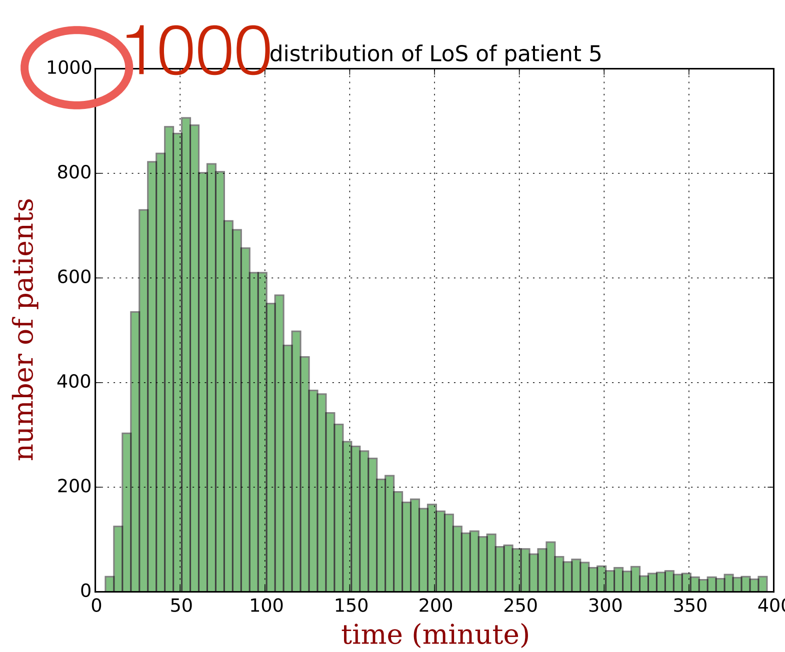
Key Performance Indicator (KPI):
Length of Stay (LoS) distribution (actual)







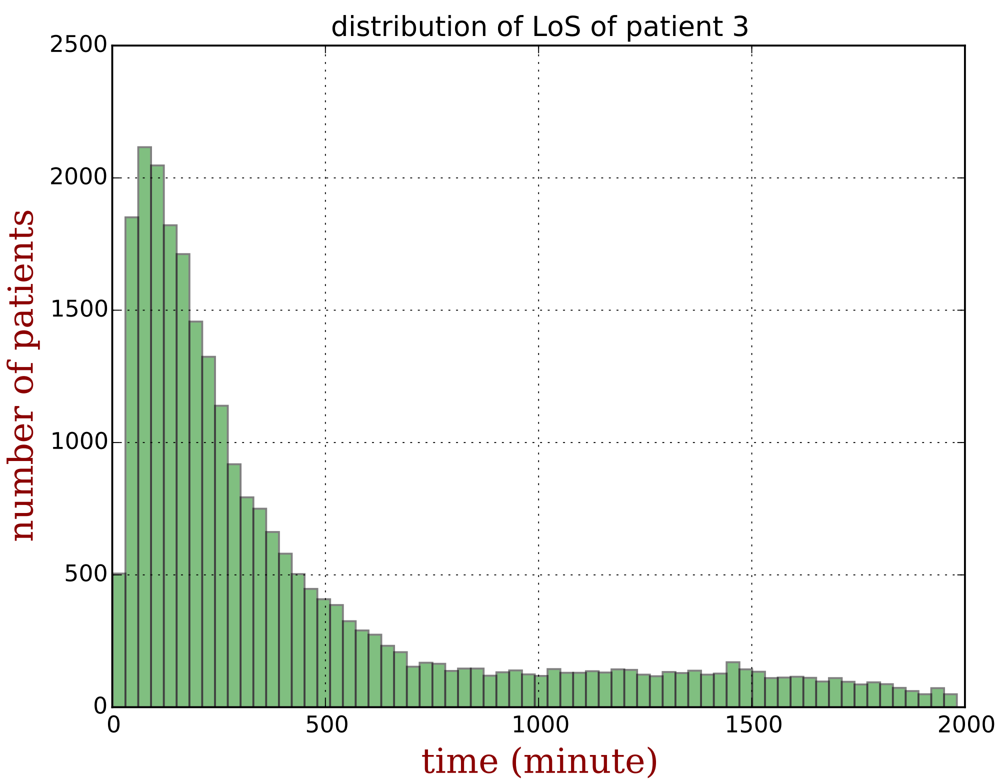




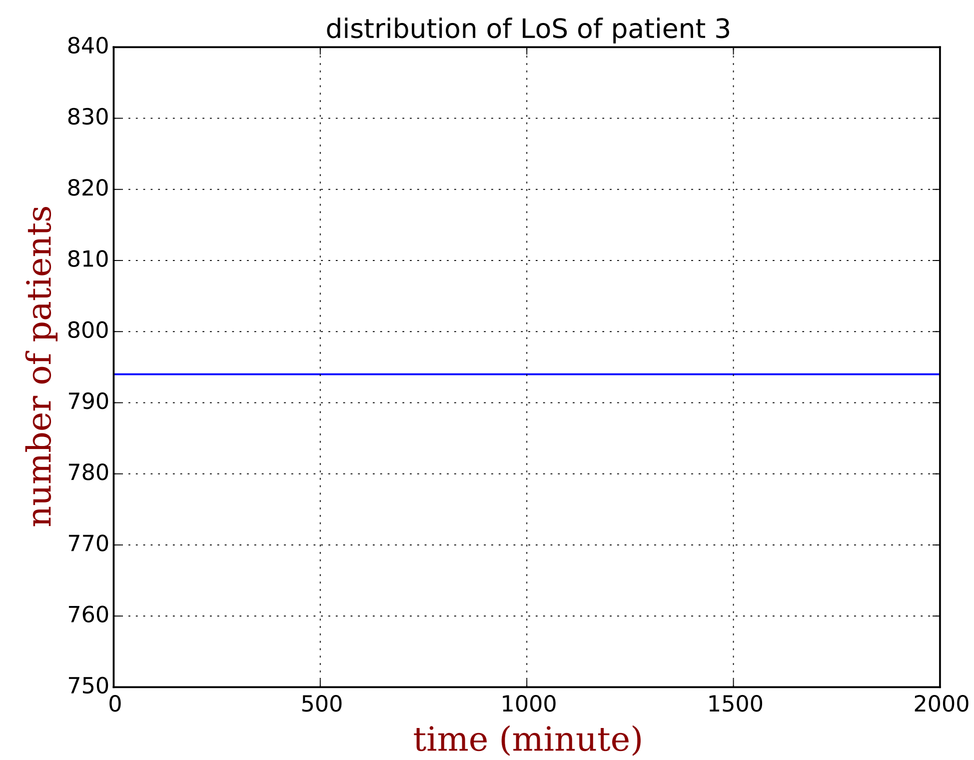
LoS distribution, better represent systematic behavior than average.

The 1st issue: results assessment

LoS **distribution**, better represent systematic behavior than **average**



Versus



The same average LoS but quite different systematic behavior.

Assess results - evaluate similarity between two distributions

In probability theory and statistics, the Jensen–Shannon Divergence (JSD) is a popular method of **measuring the similarity between two probability distributions**. The distance between simulation output and historical data measure function is defined as:

Assess results - fitness function - LoS

$$\boxed{f_{fitness} = \sum_{j=1}^{5} W_j D^j_{JS}} \qquad D^j_{JS} = \frac{1}{2} D_{KL}(P||Q) + \frac{1}{2} D_{KL}(Q||P)$$

Where, D^j_{JS} represents the Jensen–Shannon Divergence (JSD) similarity on LoS of patients with acuity level j, W_j is the weights according to patient category (acuity level) and $\sum_{j=1}^{5} W_j = 5$ (there are five patient categories), and D_{KL} denotes the Kullback–Leibler divergence (D_{KL}), which is defined as:

$$D_{KL}(P||Q) = \sum_{i=1}^{n} P(i) \log_2 \frac{P(i)}{Q(i)}, \quad D_{KL}(Q||P) = \sum_{i=1}^{n} Q(i) \log_2 \frac{Q(i)}{P(i)}$$

Where, $Q(i)$ is the frequency/probability of LoS located in ith interval extract from simulation results, and $P(i)$ denotes the same information extracted from real data. Having shown that, the range of $f_{fitness}$ function value will be 0.0 to 5.0, The lower it is, the closer the difference between simulation and actual will be.

Assess results - fitness function - LWBS

Issues:
(1) Big initial bias, system saturation, patients leave without being seen (LWBS).
(2) Percentage of LWBS should also be fitted.

$$F_{fitness}(P) = \begin{cases} f_{fitness}(P) + \lambda R_{lwbs} & (simulation\ succeed) \\ F_{max} & (system\ saturated) \end{cases}$$

Where, $P = \{p_1, p_2, \cdots, p_8\}$ denotes a parameter set from the Monte Carlo method or the optimization solver, R_{lwbs} is the ratio of patients leave-without-been-seen (range from 0 to 1.0), λ is an adjustable parameter which represent the weight of LWBS. F_{max} is the maximum penalty to the solver, which is the maximum of $F_{fitness}$ in the first case (simulation succeed). Given this, if we set λ as 5.0, that is to say, the D_{JS} similarity and LWBS have the same weight on the fitness evaluation, the value of $F_{fitness}$ will be between 0 to 10. The lower it is, the closer it will be to actual data.

The simulation-based optimization

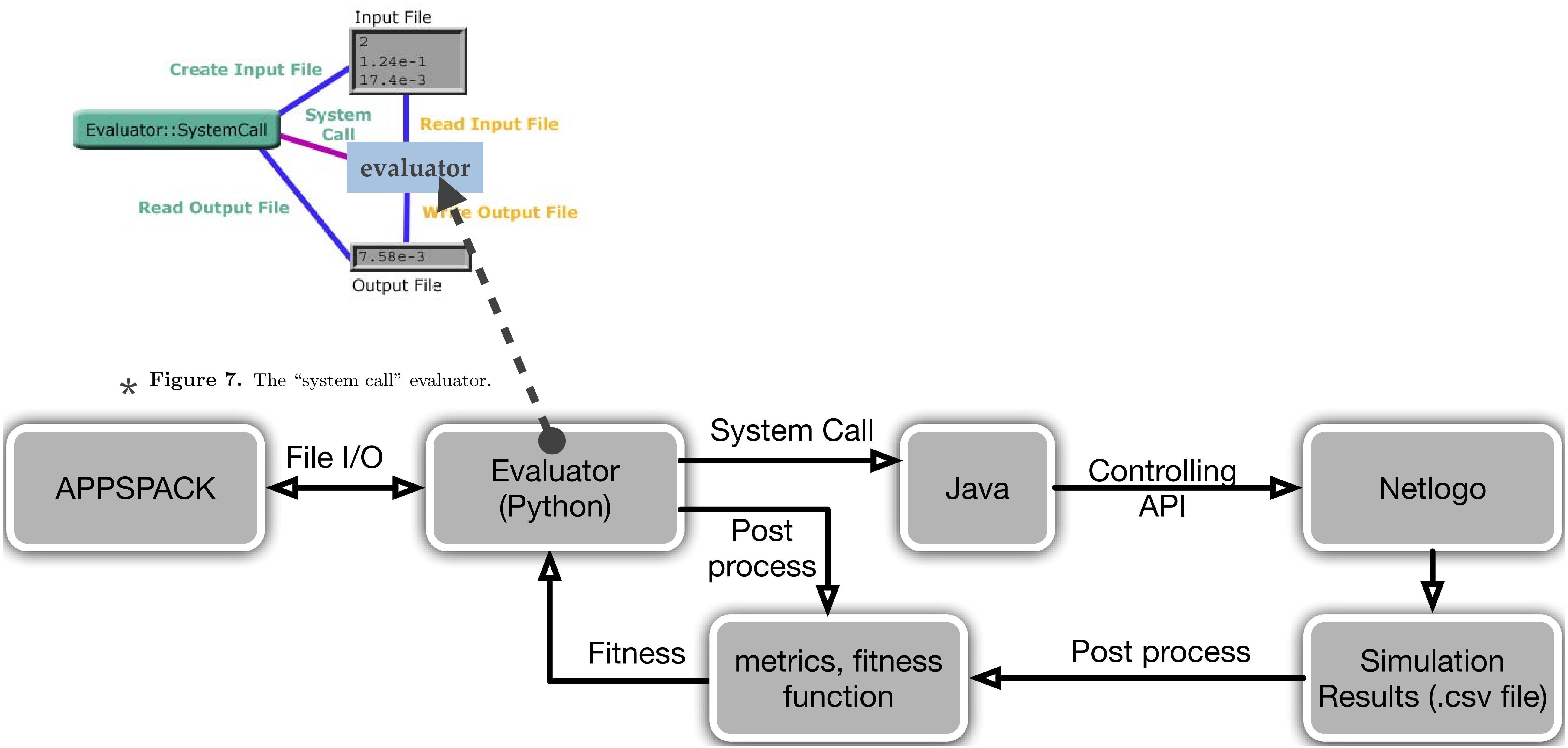
(1) Optimization without ***Gradients***
(2) Computational ***expensive*** function evaluations (~20 minutes/simulation)

Optimization - APPSPACK

A parallel optimization method is crucial for our requirement. The APPSPACK[1-3], developed by Sandia National Laboratories, implements an asynchronous parallel pattern search method that has been specifically designed for problems characterized by **expensive function evaluations**. The framework enables parallel operations using Message Passing Interface (MPI), and allows multiple solvers to run simultaneously and interact to find solution points [1-3].

[1] G.A.Gray, T.G.Kolda, Appspack4.0:Asynchronous parallel pattern search for derivative-free optimization, ACM Transactions on Mathematical Software 32(3) (2006) 485–507.
[2] T. G. Kolda, Revisiting asynchronous parallel pattern search for nonlinear optimization, SIAM Journal on Optimization 16(2) (2006) 563– 586. doi: 10.1137/040603589.
[3] J. D. Griffin, T. G. Kolda, Asynchronous parallel generating set search for linearly-constrained optimization, Technical Report, Sandia National Laboratories, Livermore, CA July 2006.

The simulation-based optimization - workflow



* **Figure 7.** The "system call" evaluator.

* in APPSPACK 4.0: Asynchronous Parallel Pattern Search for Derivative-Free Optimization, page 17.

Further accelerate searching via cache-query

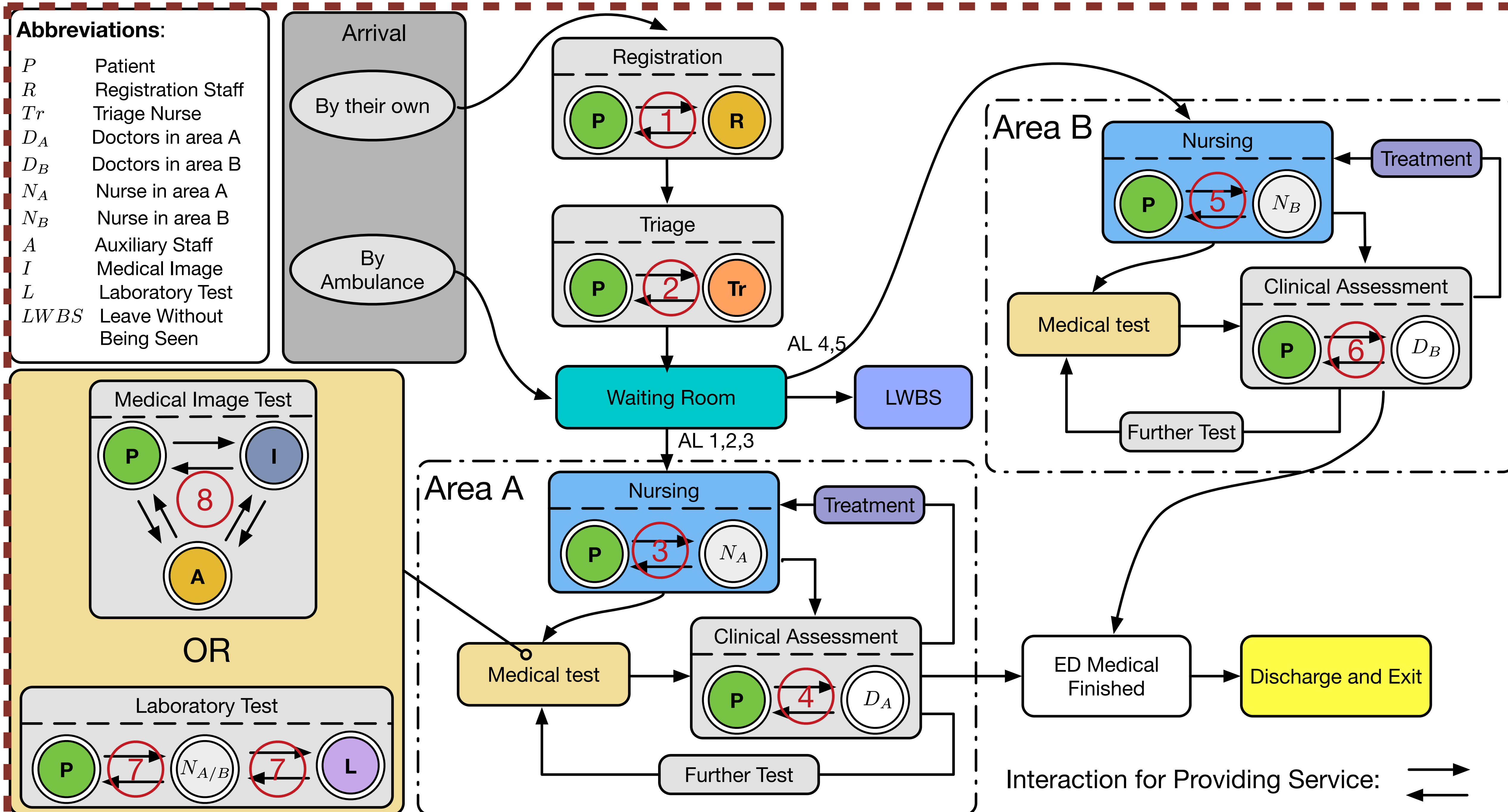
$$if \quad \exists P^{\circ} \in C_p : \quad d = \sqrt{\sum_{i=1}^{n} \left|P_i^{*} - P_i^{\circ}\right|^2 / n} < \varepsilon \quad then : \quad f\left(P^{*}\right) := f\left(P^{\circ}\right) \quad (1)$$

Where, P° is the initial value sets of one pair (initial-optimum) in collection C_p. P^{*} is the new initial value generated by the Monte Carlo method, n is the number of parameters in p_i, and ε is the tolerance. If the new initial value set is close to any of the solved pair (overlapped), it will be discarded and call Monte Carlo to generate a new initial set.

Based upon the fact that:

- The parameters to be calibrated represent the behavior of a practical agent, it is reasonable to assume that slight changes to parameters would not lead to a big difference in outputs
- Searching for local minimum is computationally expensive (hours for one process)

A case study, calibrated for Taulí



Typical missing information because it is out the scope of an information system.

A case study, calibrated for Taulí - list of parameters

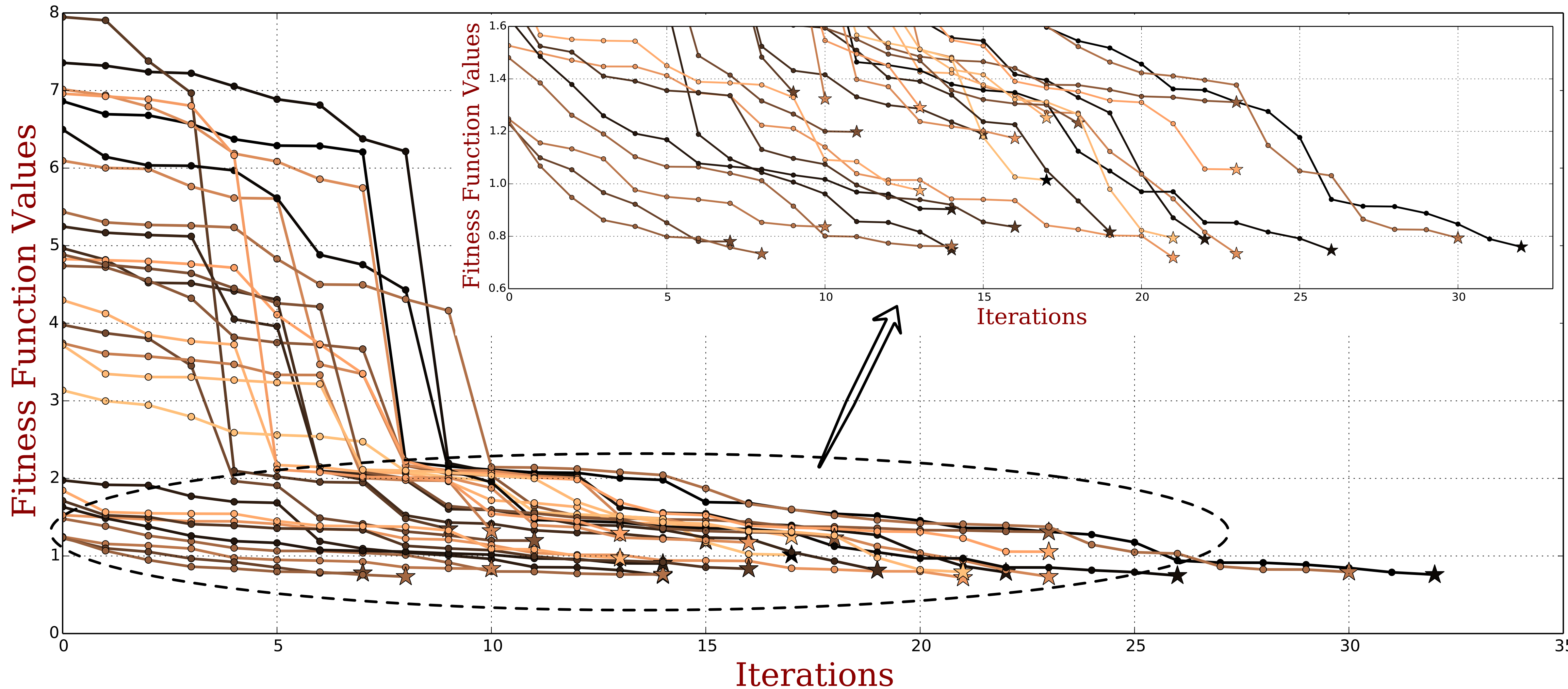
Table 1: The parameters to be calibrated for the general agent-based model of emergency departments, in order to imitate the emergency department of Hospital of Sabadell . Note: **LB** and **UB** denotes Lower and Upper Boundary respectively, **TV** represents the Typical Value; all the units of time are in minutes. The **Identity** column corresponds to the circled numbers in Figure 1 denote the type of service.

Identity	Notation	Description	LB	UB	TV
1	$T_{service}^{register}$	the parameter for registration service-time distribution model.	2	15	5
2	$T_{service}^{triage}$	the parameter for triage service-time distribution model.	5	20	10
3	$T_{service}^{nurseA}$	the average duration of service of nurses in area A.	8	30	16
4	$T_{service}^{doctorA}$	the average duration of service of doctors in area A.	8	30	18
5	$T_{service}^{nurseB}$	the average duration of service of nurses in area B.	5	20	12
6	$T_{service}^{doctorB}$	the average duration of service of doctors in area B.	5	20	15
7	$T_{service}^{imaging}$	the average duration for taking medical imaging.	20	40	25
8	$T_{service}^{lab}$	the average duration for taking laboratory test sample.	10	30	15

The optimization process - convergence

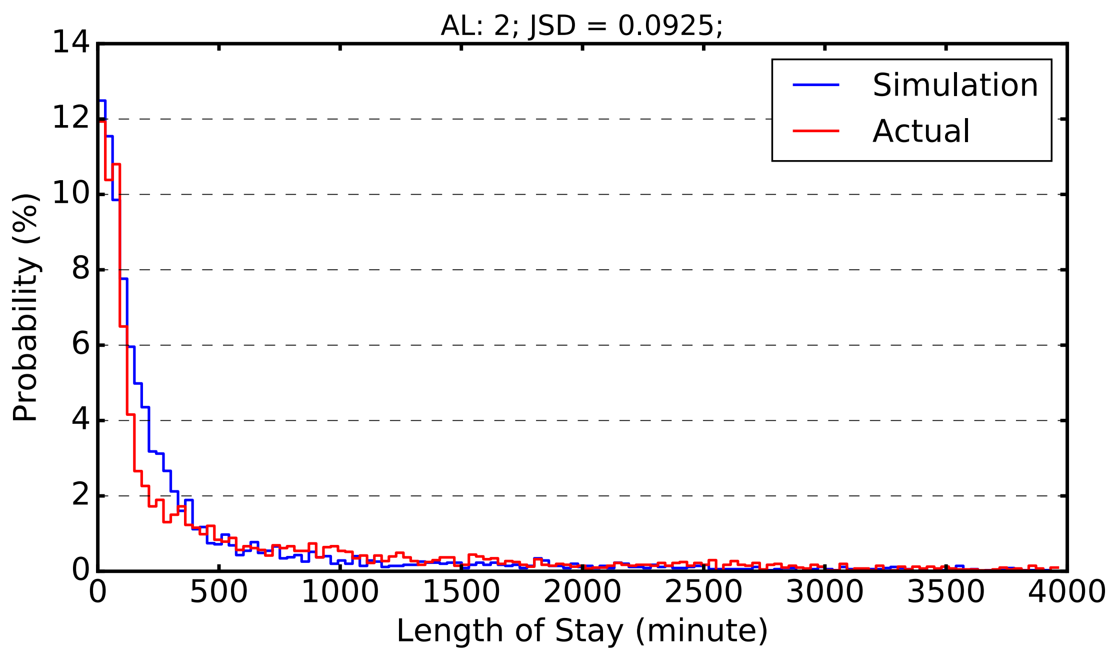
Conditions: The calibration was carried out on an 8-node cluster with total number of 512 AMD OpteronTM Processor 6262 HE cores, and 2TB RAM. All the nodes works in master/worker way, i.e., each one of the node (worker) runs the parallel version of APPSPACK.

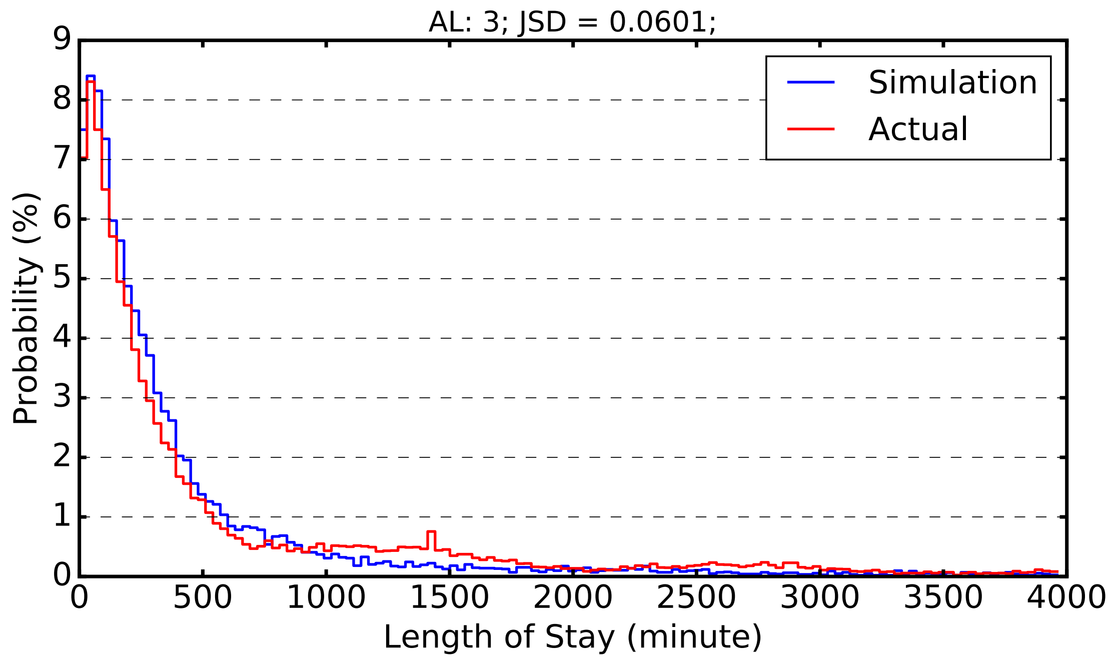
Time: ~70 hours

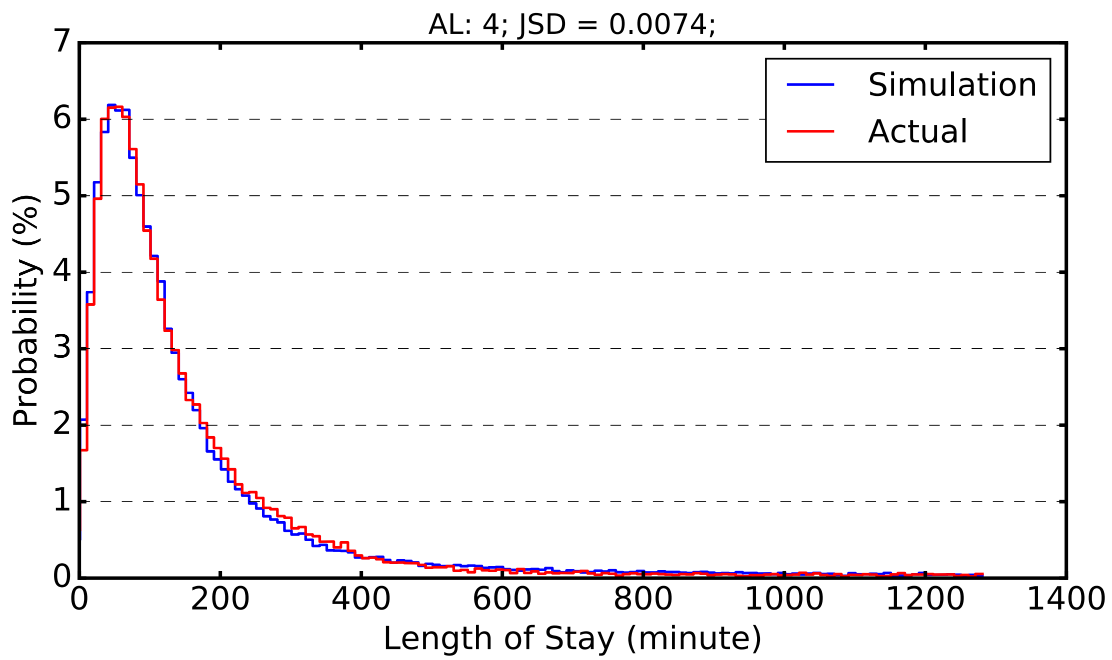


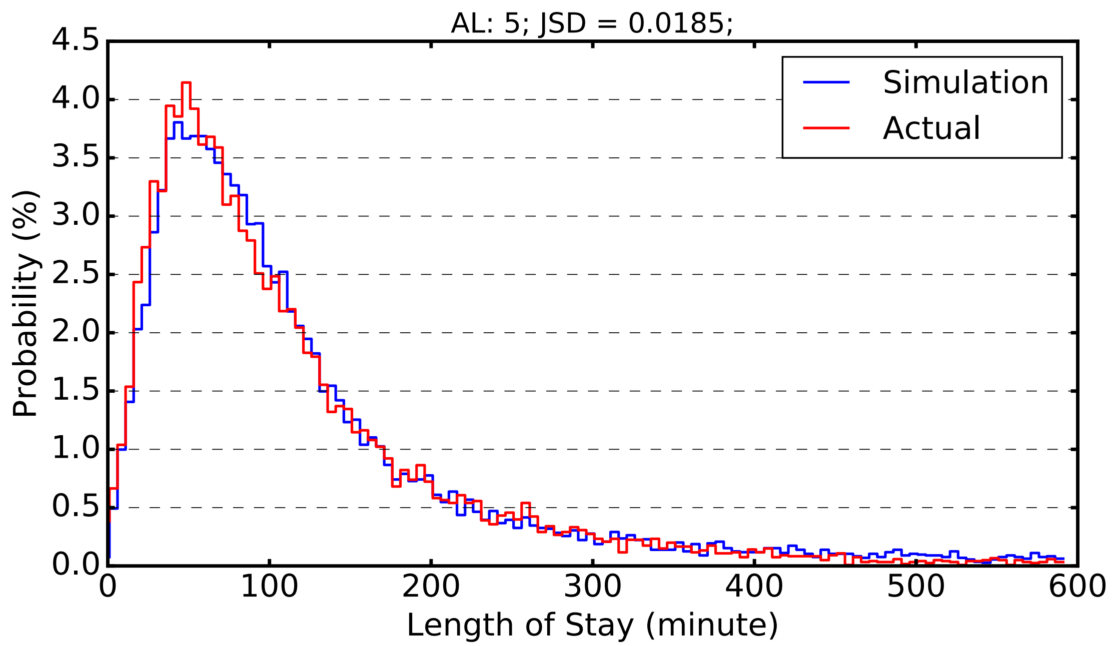
Fitness optimization on training dataset with different initial value, fitness values versus iterations. One broken line represents one optimization process with a given starting point from boundary constrained Monte Carlo.

The calibration results - model validation









Set up your own simulator, you need…

UAB

Set up your own simulator, you need…

from your **information system**

Patient: arrival hour, day, acuity level, discharge time(date-time)

System configuration: #doctor, #nurse, #labs (machine), #medical image, … (all about the *resource* you have)

from your **experience**

Table 1: The parameters to be calibrated for the general agent-based model of emergency departments, in order to imitate the emergency department of Hospital of Sabadell . Note: **LB** and **UB** denotes Lower and Upper Boundary respectively, **TV** represents the Typical Value; all the units of time are in minutes. The **Identity** column corresponds to the circled numbers in Figure 1 denote the type of service.

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4	$T^{doctorA}_{service}$	the average duration of service of doctors in area A.	8	30	18
5	$T^{nurseB}_{service}$	the average duration of service of nurses in area B.	5	20	12
6	$T^{doctorB}_{service}$	the average duration of service of doctors in area B.	5	20	15
7	$T^{imaging}_{service}$	the average duration for taking medical imaging.	20	40	25
8	$T^{lab}_{service}$	the average duration for taking laboratory test sample.	10	30	15

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6	$T^{doctorB}_{service}$	the average duration of service of doctors in area B.	5	20	15
7	$T^{imaging}_{service}$	the average duration for taking medical imaging.	20	40	25
8	$T^{lab}_{service}$	the average duration for taking laboratory test sample.	10	30	15

+

The tool and general model

UAB

Set up your own simulator, you need…

from your information system

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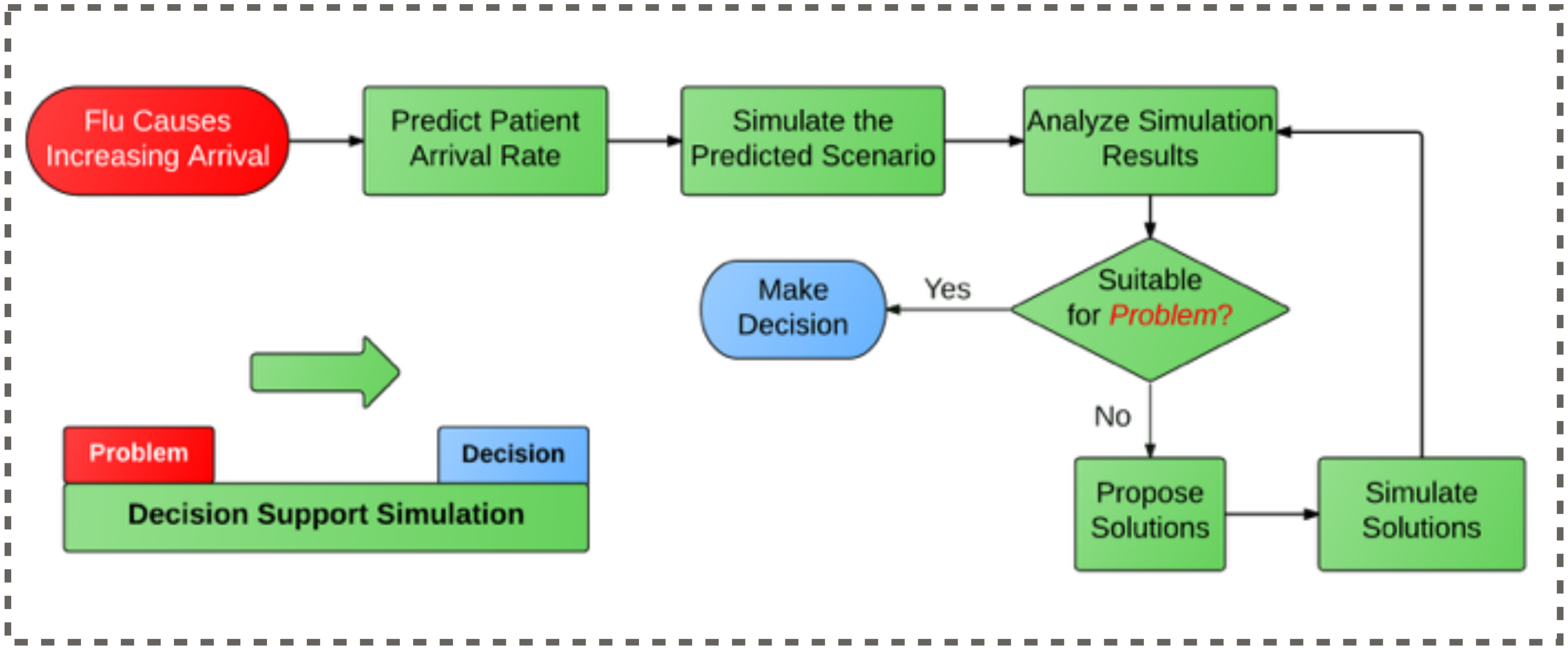
+

The tool and general model = **value of parameters to set up your simulator (for your system)**

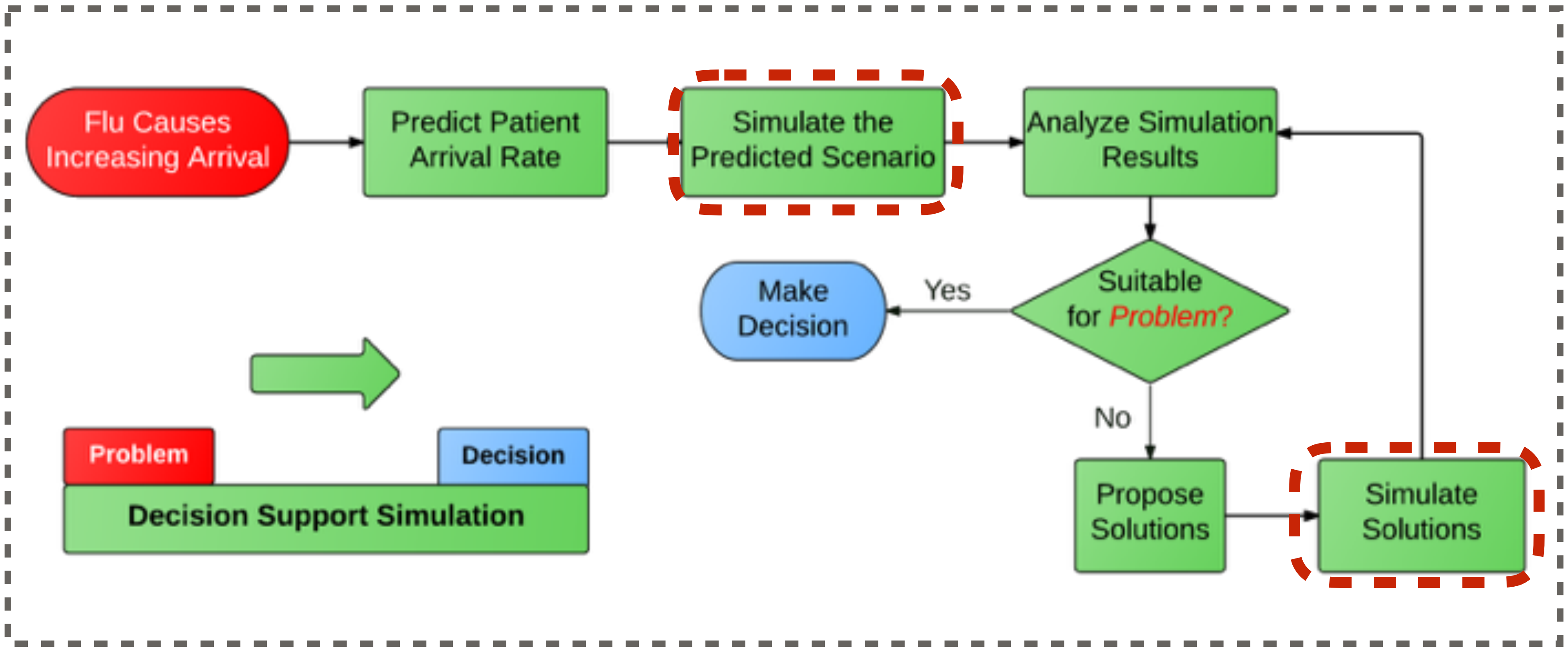
- Introduction
- The general emergency department model
- Model parameters calibration under data scarcity
- ***Decision support examples***
- Conclusion, future work & related publications

from the problem to decisions

from the problem to decisions



from the problem to decisions



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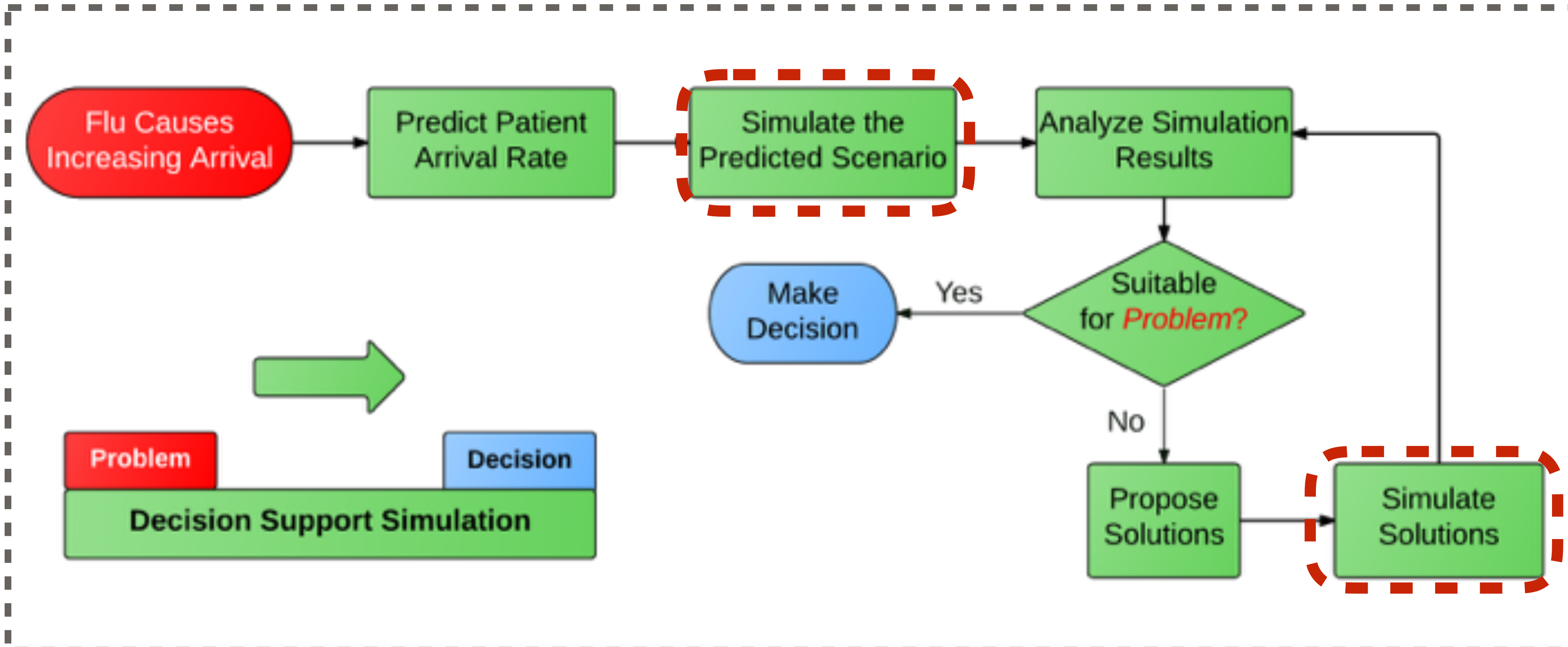
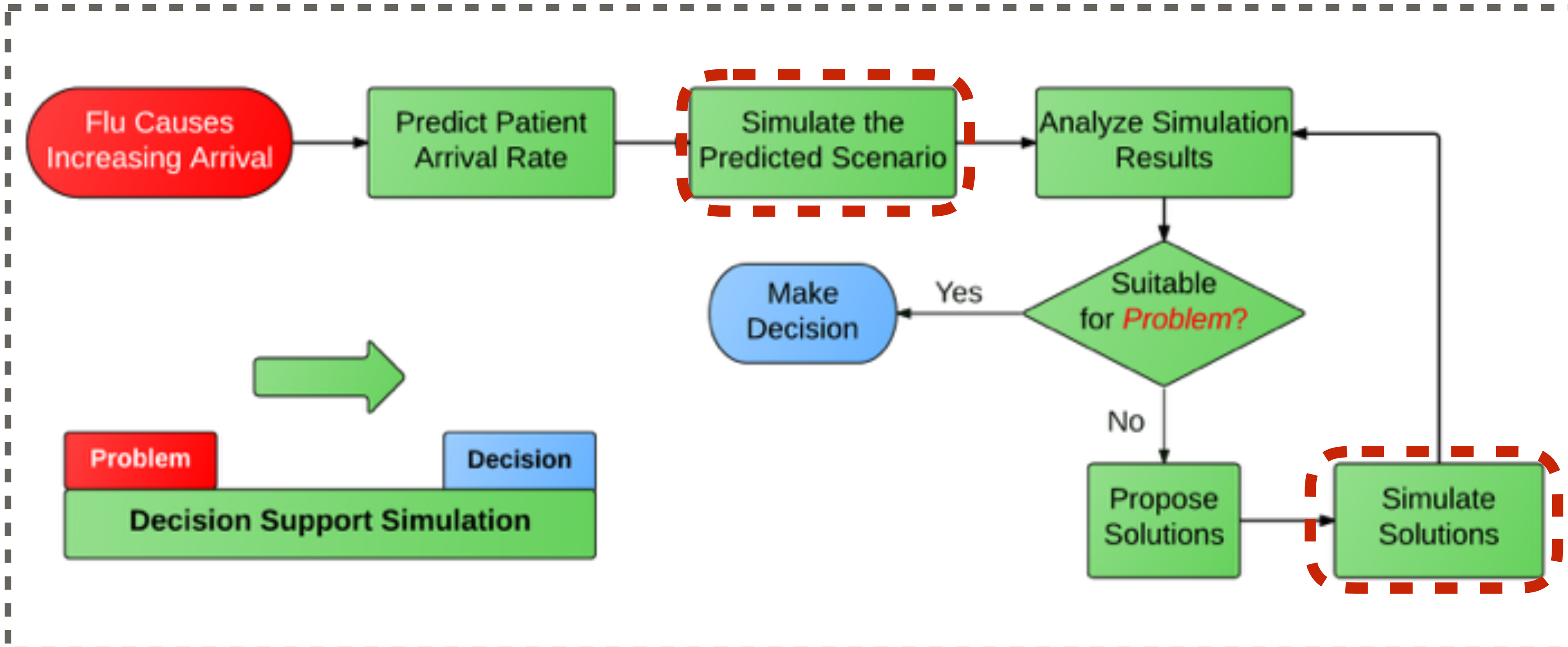


Information for making decision, you demand it, the tool dedicates it.

from the problem to decisions



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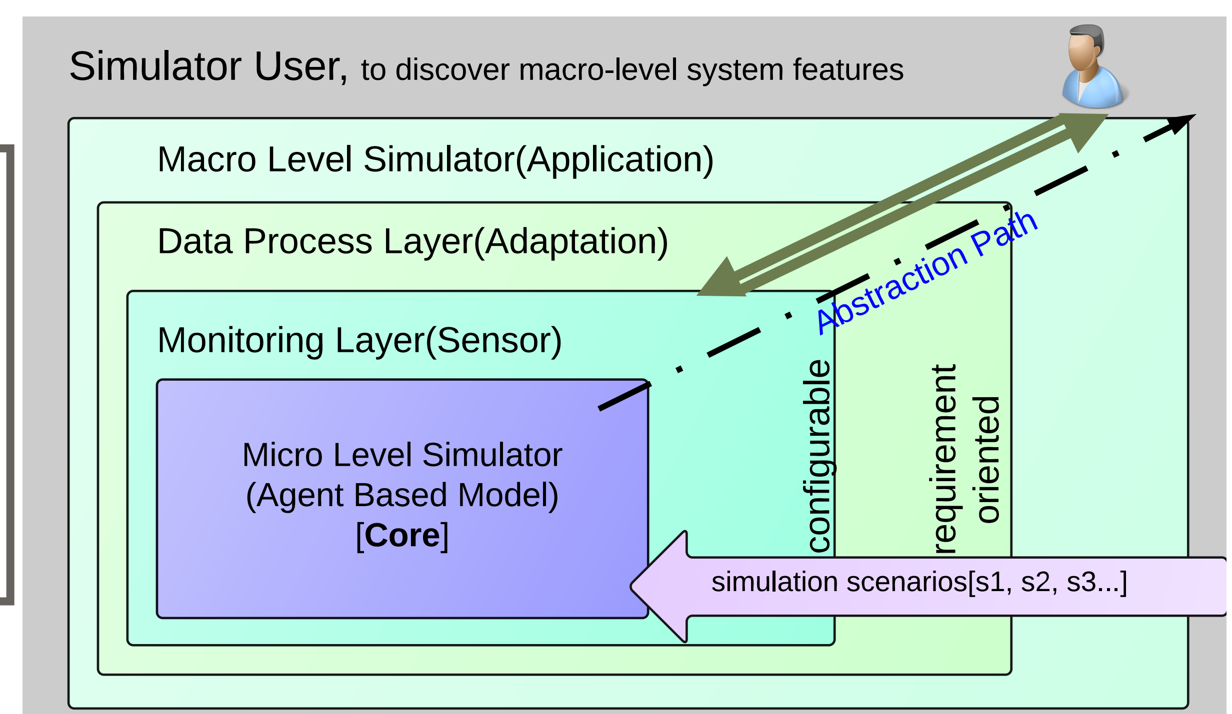

Case study 1

Decision Support for Continuously Increasing Patients Arrival

1. Determine system bottleneck
2. Quantify cost-and-effect of proposals
3. Decision support

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

Case study 1

Case study 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	10.30	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

Case study 1

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Add two more technicians to laboratory room

Daily arrival	Average LoS by acuity level(hour)					Average utilization of ED resources(%)				
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476	12.54	12.70	14.33	3.80	3.57	64.19	55.04	92.30	73.01	59.42
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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	64.30
535	11.26	11.31	12.54	4.36	5.82	71.39	60.65	76.00	82.52	67.14

Case study 1

LoS and ED resources utilization with increasing arrival patient

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Add two more technicians to laboratory room

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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
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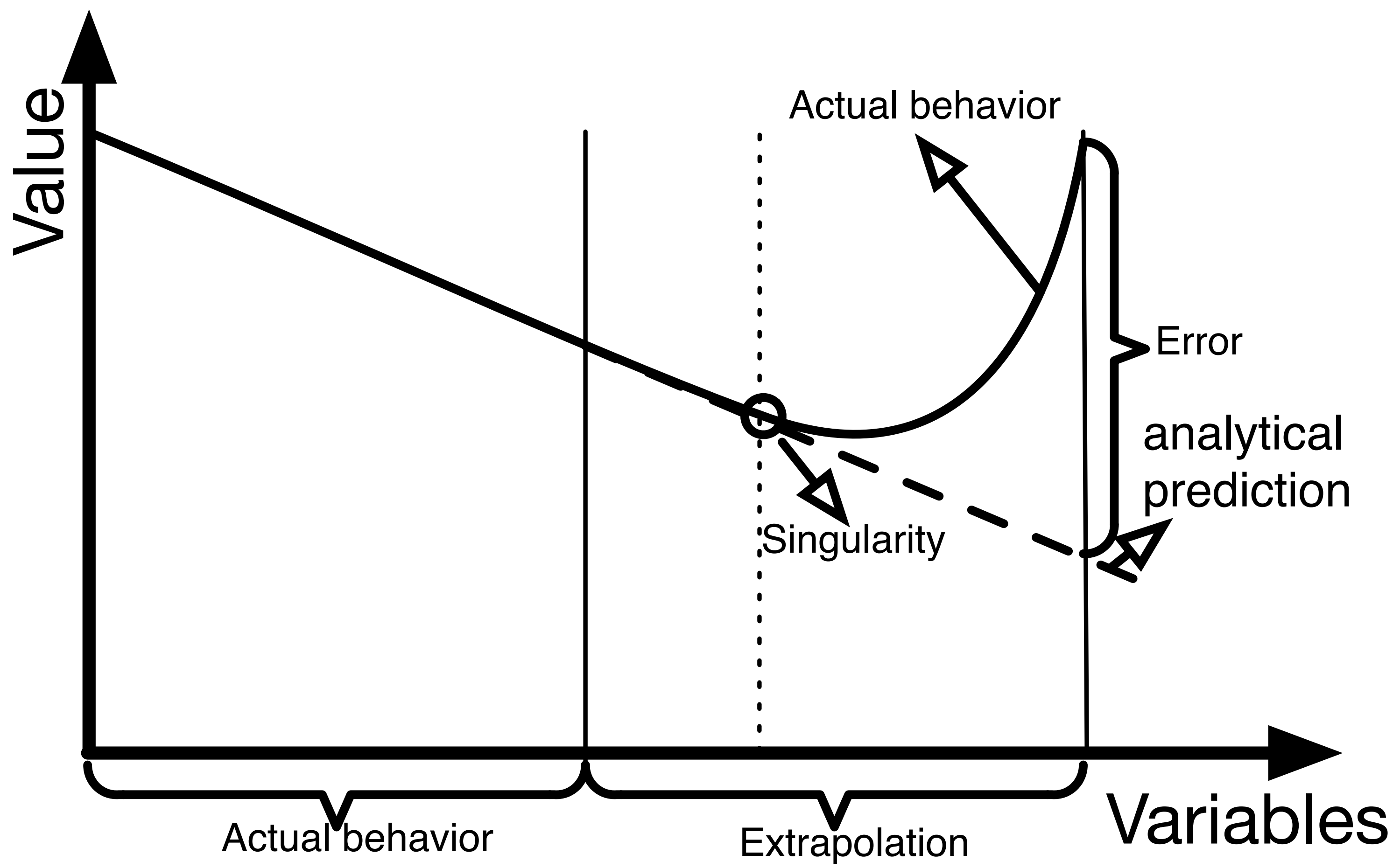
Two more doctors added to area A

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	64.30
535	11.26	11.31	12.54	4.36	5.82	71.39	60.65	76.00	82.52	67.14

Gradually add resources to get optimum all the time

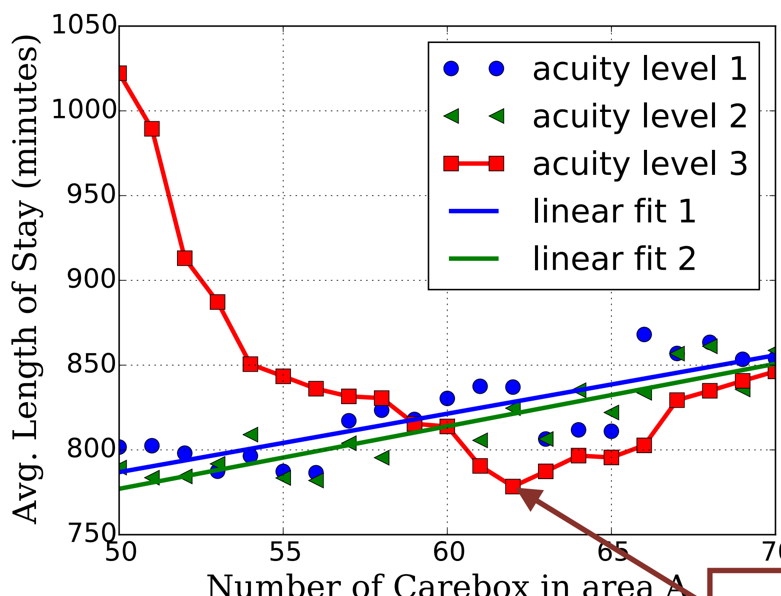
Case study 2

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

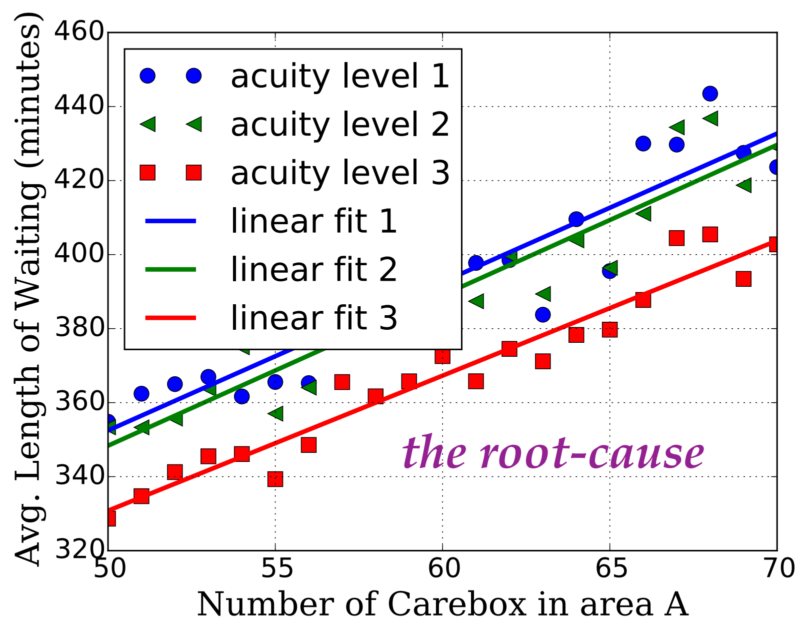


Case study 2 — cost-and-effect predictions

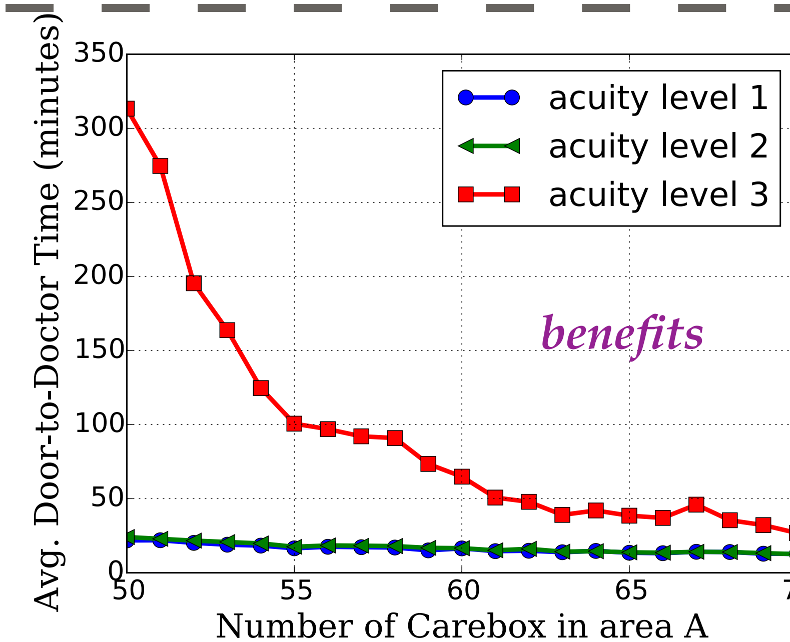
The influence of additional carebox on patients' behavior (Area A).



(a) length of stay



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



(c) door-to-doctor time

Conclusions

Key contributions:

- An agent-based model for quantitatively predicting and analyzing the complex behavior of emergency departments (*general & adaptable, published in SIMUL 2014, the extended version has been submitted to simulation Modelling Practice and Theory for peer-review*).
- Developed analytical methods and tools that can be used to understand and manage complex systems. (*published in 2015 International Conference on Computational Science and 2015 Winter Simulation Conference*)

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Healthcare, Medical Informatics

Future Research Directions

- Do statistical **sensitivity analysis** of the variables of the emergency department simulator. The variable sensitivity information could be used to build a knowledge base or a metamodel (model of a model) of EDs.
- Connect the emergency department simulator with the hospital to study **disordered system behavior** based on the integration of first-principles model and data-driven model (with real operation data).
- Calibrate the general model for all EDs in a regional area and, connect these simulators together for short-term (several hours) **occupancy prediction**. Then, a load balancing scheme of the incoming patients could be designed based on these future occupancy predictions.
- The framework developed in our work could be used to build a full model of **integrated care system**. Similarly, it will be able to represent a comprehensive tool to quantitatively evaluate prospective planned changes to the integrated care system for decision making.

Thank you for your attention!

谢谢(Xiè Xiè)！

¡Gracias!

¡Gràcies!