

# Evaluating the dispatching policies for a regional network of Emergency Departments exploiting Health Care Big Data

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# The Emergency Department overcrowding

The **Emergency Department (ED)** is a sub-unit of the hospital that operates 24/7, providing immediate treatments to (non-elective) patients.

An international issue concerning the ED is the **overcrowding**.

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- ▷ **Peaks of demand**
- ▷ Patients self-referral
- ▷ High variety of pathologies
- ▷ Inadequate staffing
- ▷ Hospital bed shortages

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## CONSEQUENCES:

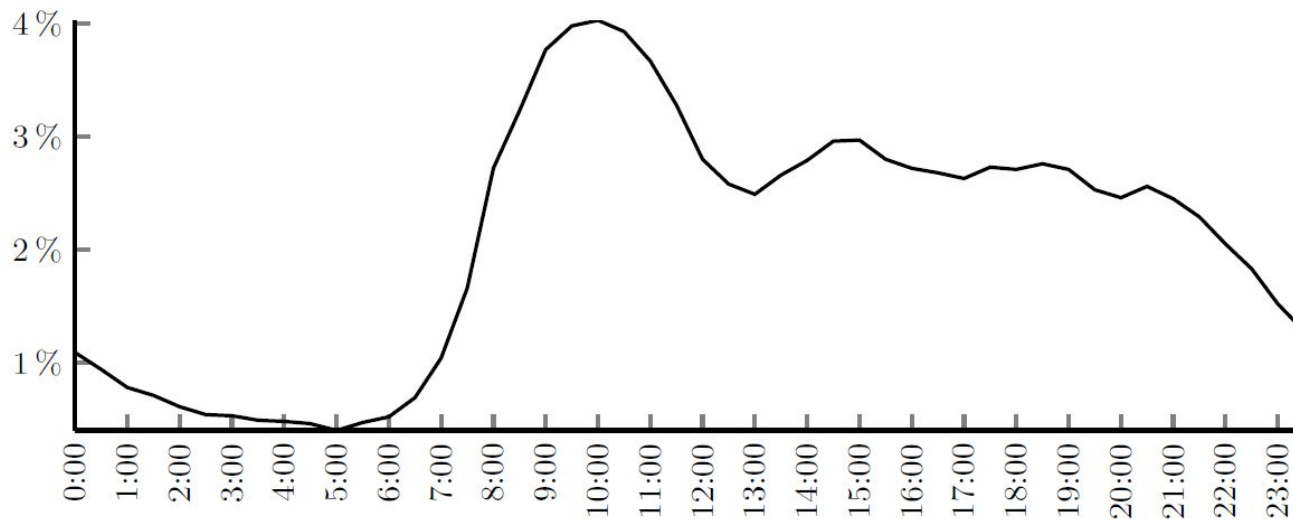
- ▷ Higher risk of medical errors
- ▷ Delays in treatments
- ▷ Patients leaving without being seen (LWBS)
- ▷ Financial losses

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# The emergency demand

Distribution of the **patient arrivals** during the day (Piedmont region, July 2011):



Two main arrival mode:

- ▷ by **Emergency Medical Service (EMS)** ambulances
- ▷ autonomously

# The regional network of Emergency Departments

At the *regional level*, the ED system can be seen as a **network of EDs** cooperating to maximise *outputs* and *outcomes*.

EMSs usually do not take into account the **ED workload level**: **dispatching policies** can be adopted with the aim to balance the emergency demand among the EDs of the network.

In order to replicate the behavior of such ED network, we need to choose a **simulation methodology**.

# The disptching problem



# The disptching problem



ambulance  
station



emergency



ambulance  
station



ambulance  
station



# The disptching problem



ambulance  
station



emergency



ambulance  
station

assignment



ambulance  
station

# The disptching problem



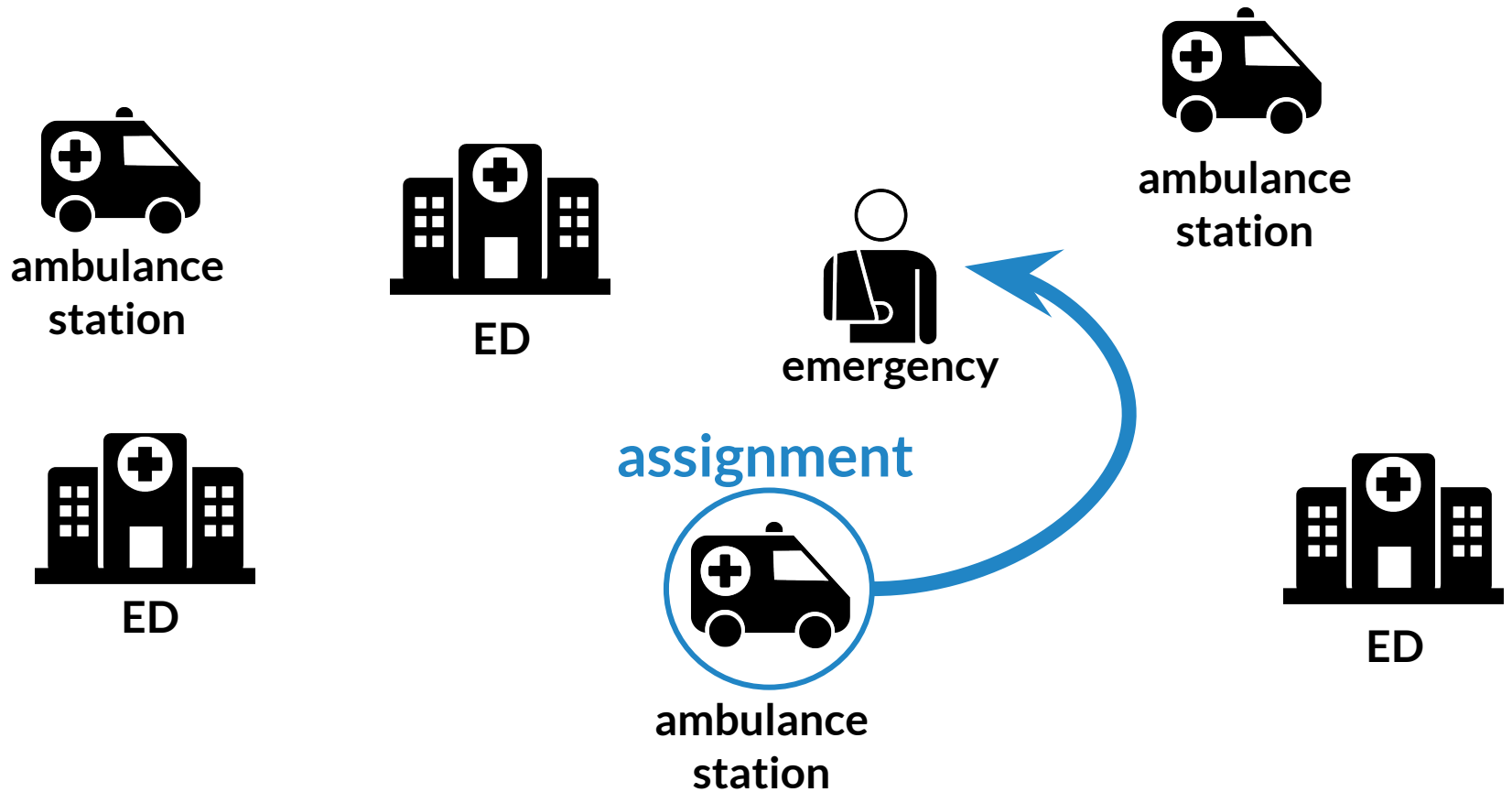
assignment



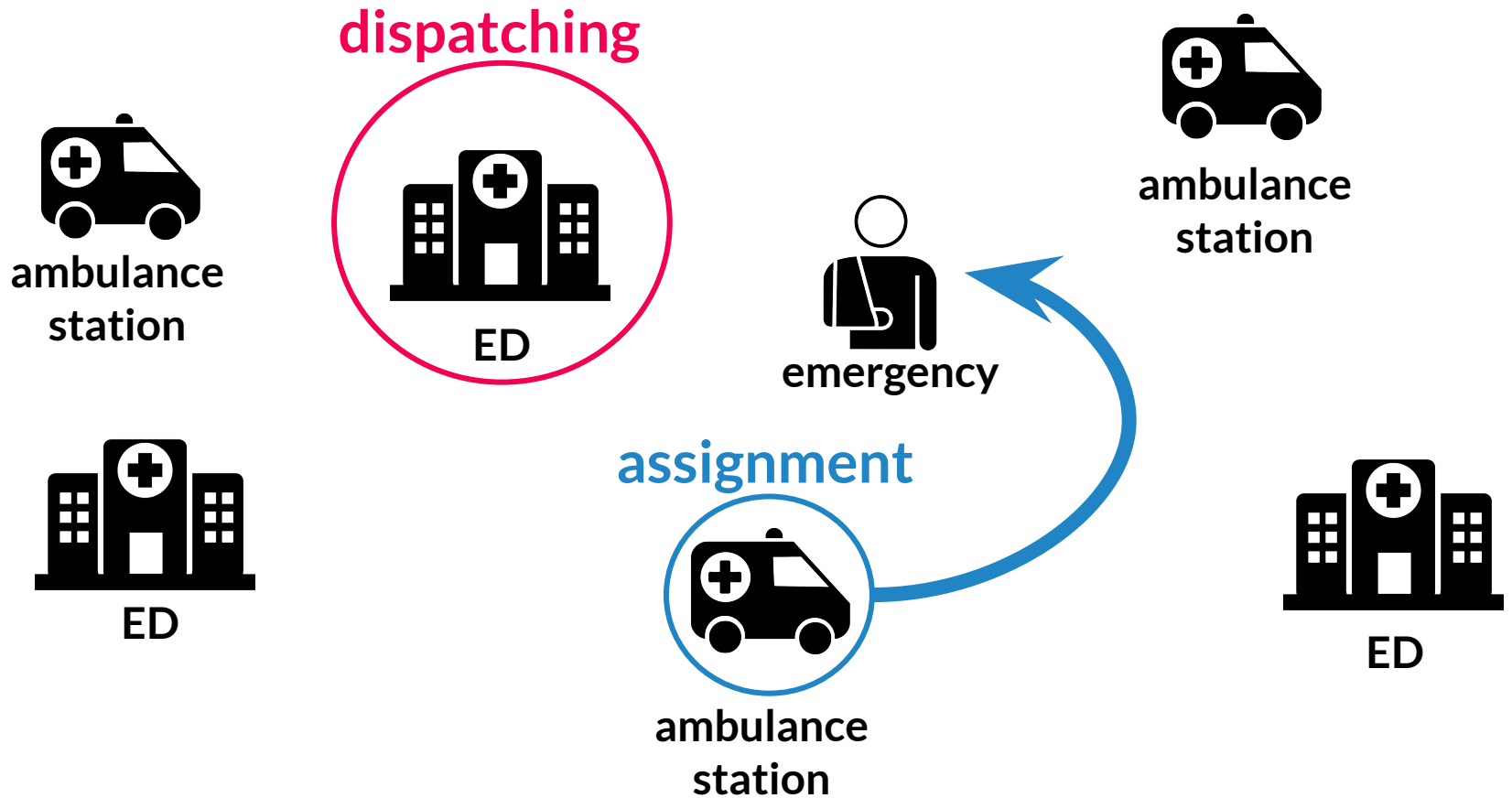
ambulance  
station



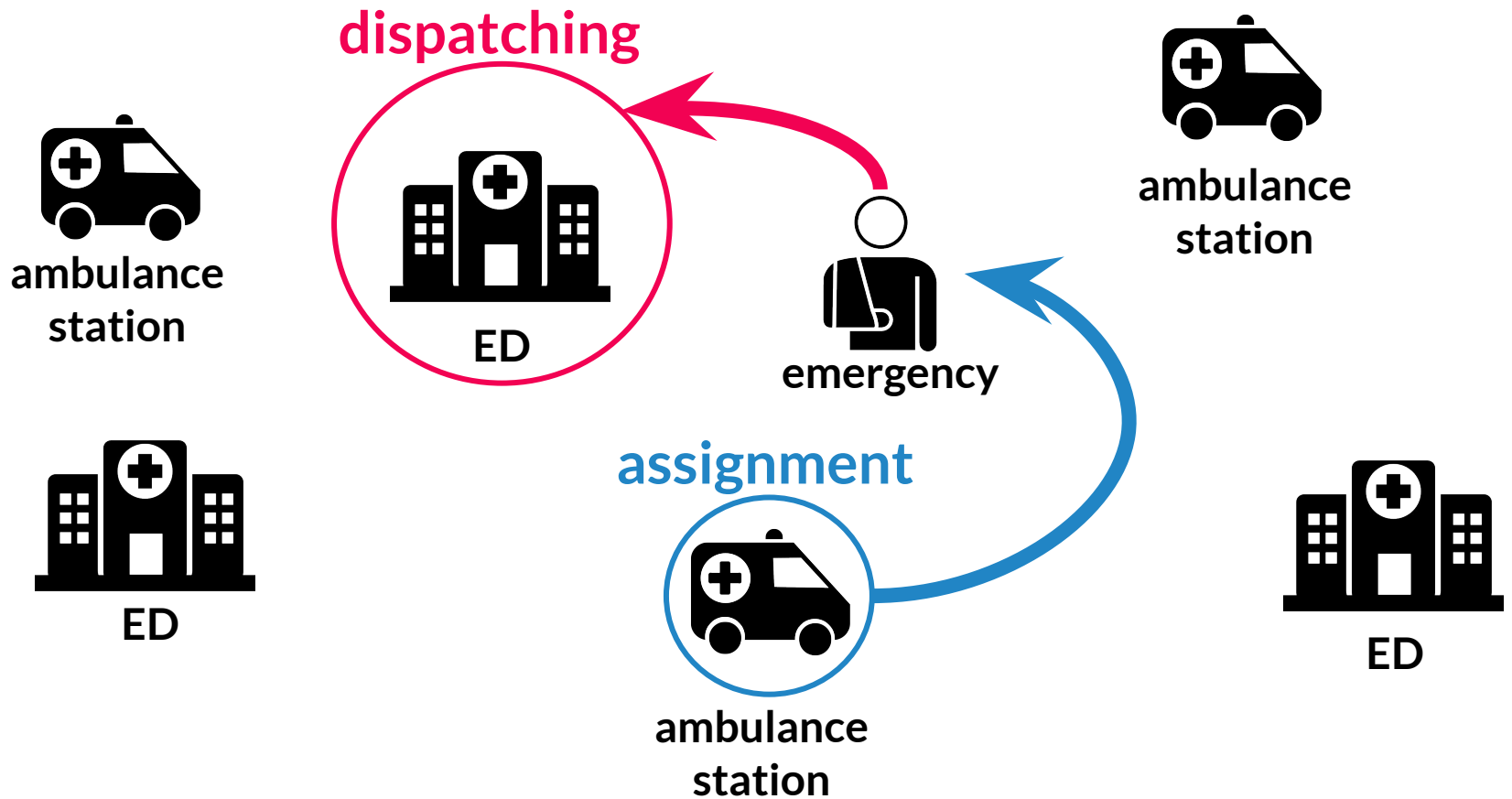
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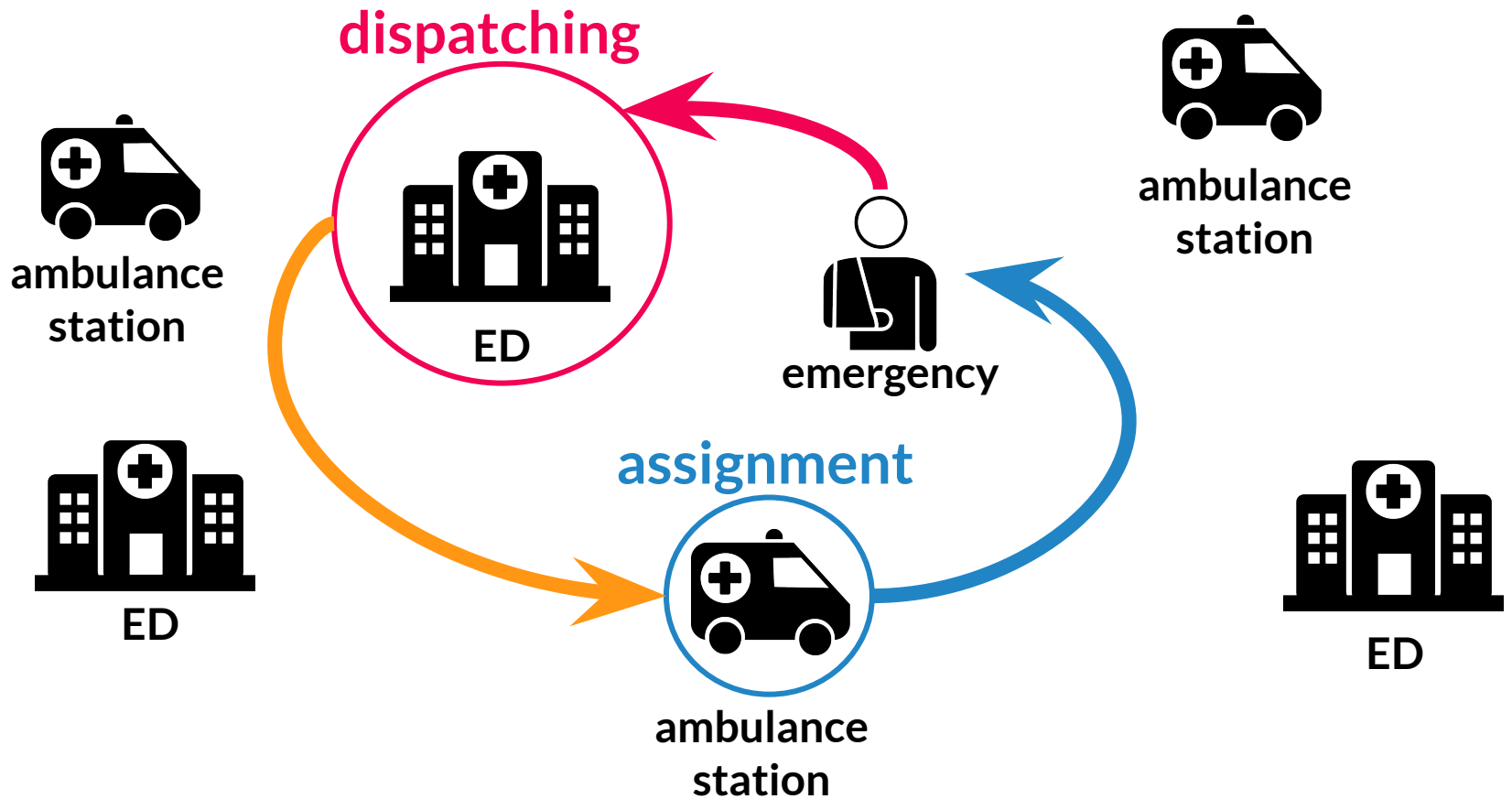
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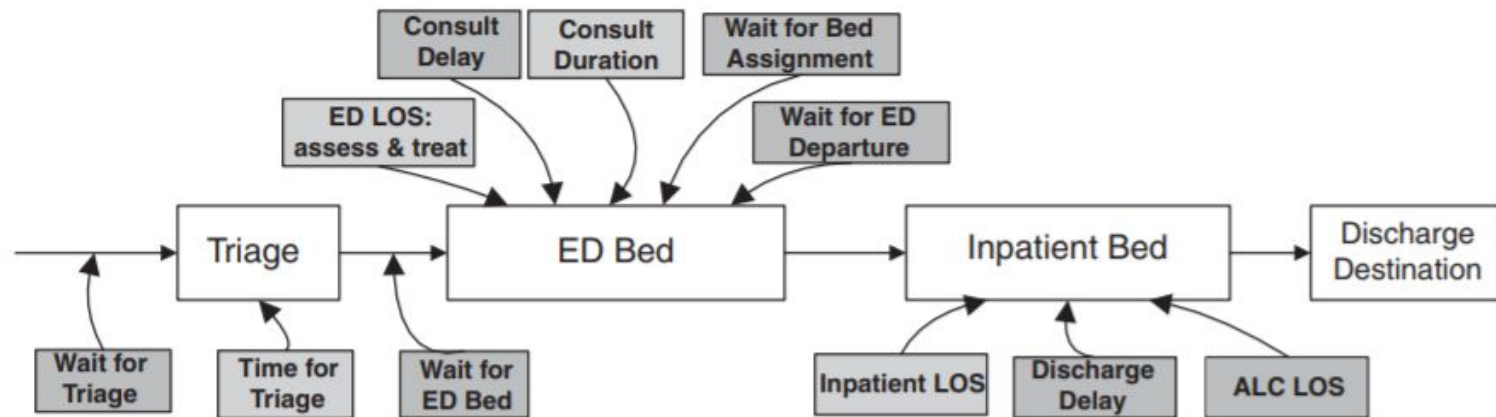


# The simulation methodology: SD

The simulation methodology most used in the literature is **System Dynamics (SD)**<sup>1</sup>, whose main elements are:

- ▷ **stocks:** entities that accumulate or deplete (e.g. waiting list)
- ▷ **flows:** rates of change of the stocks (e.g. insertion rate)

## Example:



<sup>1</sup> Vanderby, S., Carter, M.: An evaluation of the applicability of system dynamics to patient flow modelling. Journal of the Operational Research Society 61(11), 1572-1581 (2010)

# The simulation methodology (SD vs. DES)

*«SD is commonly used to assess and understand patient flow and resource demand from a more strategic, and therefore aggregate, perspective»<sup>1</sup>*

## Limitations:

1. **Patient are indistinguishable.** Health care services are generally characterised by a large variety of patients flowing in the same **care pathway (CP)**
2. Our problem arises at the **operational level** (short term)

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**Discrete Event Simulation (DES)** is more appropriate from this point of view:

- ▷ representation of each **single patient** within the CP
- ▷ application of **optimisation algorithms**

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# Health Care Big Data

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*Fortunately, nowadays huge amounts of data are collected by hospitals, recording accesses, diagnosis and treatments of patients.*

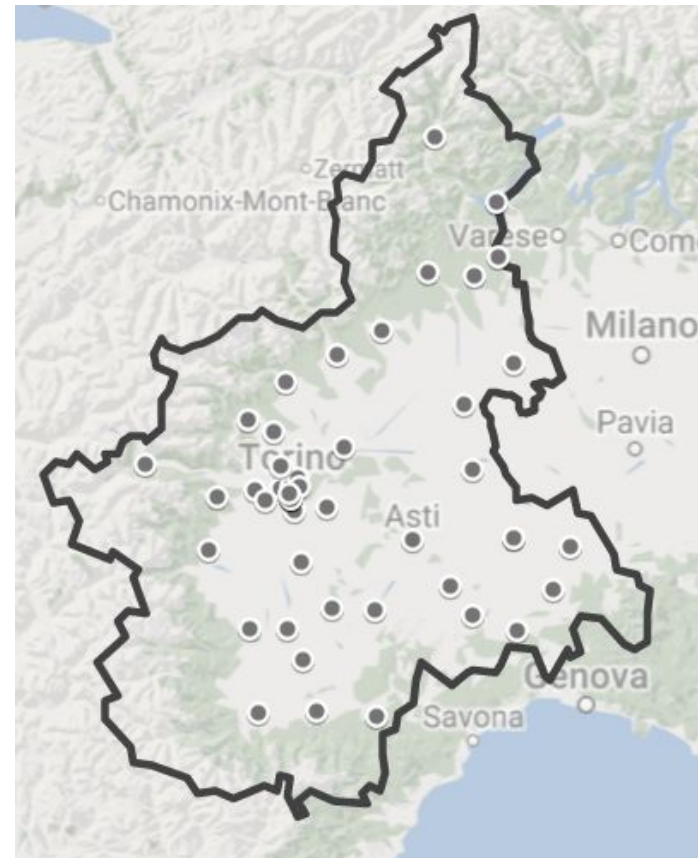
**Health Care Big Data (HCBD)** can power a health system analysis using DES methodology.

**Issue:** data is usually recorded for clinical, legal or administrative purposes, that is not exactly our perspective.

# The ED network in Piedmont region

**Piedmont** is an Italian political region, with an surface of 25,402 km<sup>2</sup> and a population ~4.6 millions, half of that lives in **Province of Turin**.

There are **49 EDs** operating on the regional network. The **waiting time** for a **urgent** and a **non-urgent** code could exceed respectively **60'** and **450'**, in the worst case<sup>1</sup>.



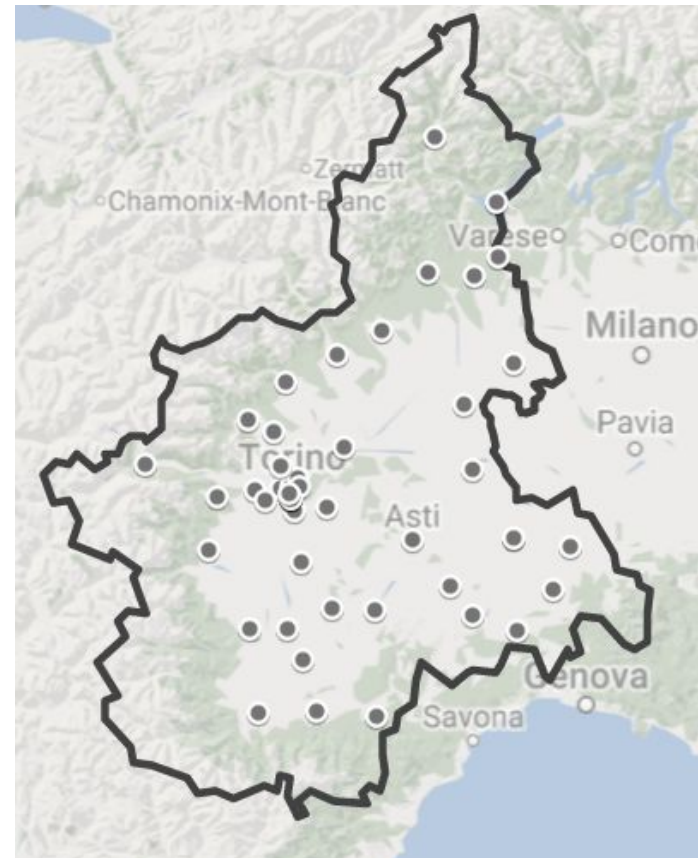
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**In similar regions they both are ~20% lower.**



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# The regional HCBD

From >10 years, Piedmont region is collecting **data** about the **regional health system** and released a regional law to unify the flows of data (**standard format** and **consistency** checked for **financial reasons**).

The **regional HCBD** contains information regarding the **ED access**: e

- ▷ encrypted patient ID
- ▷ patient residence (city, postal code)
- ▷ timestamps (arrival, admission, discharge, ...)
- ▷ urgency code (1 to 4)
- ▷ ED facility
- ▷ Treatments

There are **~1.8 millions of accesses per year**, of which:

- ▷ **~90% non-urgent cases** (urgency code 3 or 4)
- ▷ **~14% are transported by the EMS** (usually to the *closest* ED)

# Aim of the work

In this study we analyse different **dispatching policies** for **non-urgent patients** located in areas from which two or more **EDs** can be reached in a **short time**.

There are two novelties in this work:

- ▷ the study of the dispatching problem through a model for a regional ED network
- ▷ the use of the **DES methodology** for the health system analysis exploiting the **HCBD**, in order to better represent the variety of the patients accessing the health system.

# A DES model powered by HCBD

We propose a **quantitative model** for the analysis of the network of EDs operating in Piedmont. The proposed model operates on a **time horizon of one month** and is organised in **two phases**:



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**PHASE 1 - Dynamic estimation of the parameters (Python 2.7)**: several **parameters** and **empirical distributions** are computed to represent

- ▷ characteristics of **patients**
- ▷ behaviour of the **ED network**

w.r.t. the time and demography (in the fixed time horizon).

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**PHASE 2 - DES model representing the emergency pathway (AnyLogic 7.2)**: parameters from PHASE 1 are used by a DES model that generates the **emergency demand** (with *uncertainty*) and replicates the ED network behavior adopting a certain **dispatching policy**.

# Quantitative model: phase 1

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**Service time (empirical) distribution:** length-of-stay (EDLOS) estimation for each ED and for each urgency class

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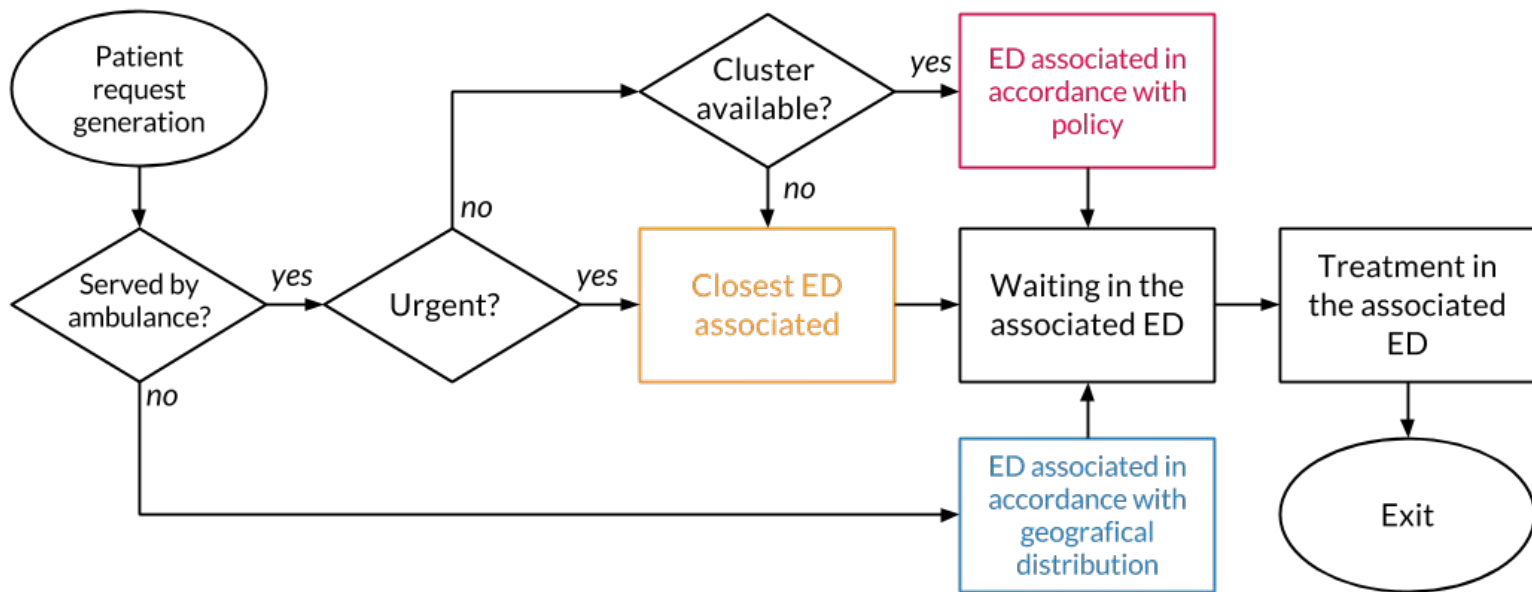


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# Quantitative model: phase 2

The **DES model** is the straightforward implementation of the following *flowchart*, which describes the **emergency pathway**:



# A DES model powered by HCBD

In this study we compared two simple **policies**:

**Policy  $P_0$  (real case)** associates the ED in accordance with **geographical distribution** (usually the closest ED is assigned).

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**Policy  $P_0$  (real case)** associates the ED in accordance with **geographical distribution** (usually the closest ED is assigned).

**Policy  $P_1$  (workload balance)** associates the ED with the minimum

$$r_h^t = \frac{w_h^t + s_h^t}{c_h},$$

with  $w_h^t$ ,  $s_h^t$  and  $c_h$  number of waiting patients, number of served patients and capacity of  $h$  at the time  $t$  (waiting time of), among those with a travelling time limit of 30 minutes.

*Note that we can introduce and analyse as many policies as we want.*

# The ED clusters

Policy  $P_1$  acts on 5 ED clusters:

$C_1$ : Area of Turin (20 EDs)

$C_2$ : Area of Alessandria (7 EDs)

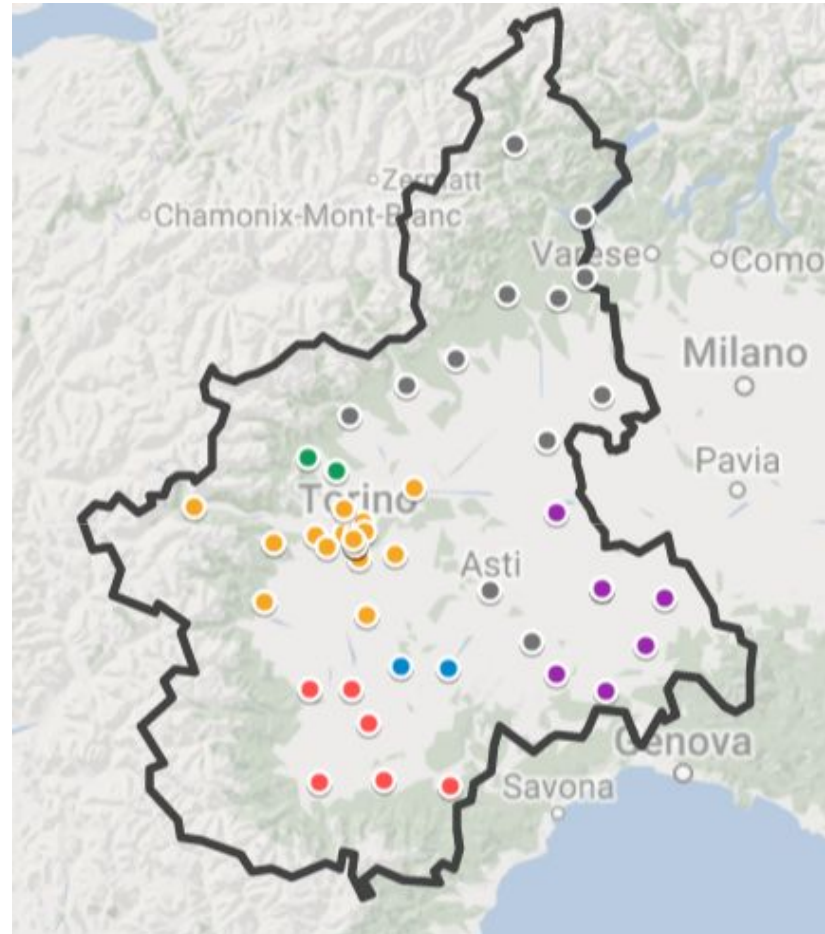
$C_3$ : Area of Cuneo (6 EDs)

$C_4$ : Lanzo valleys (2 EDs)

$C_5$ : Area of Barolo & Tartufo (2 EDs)

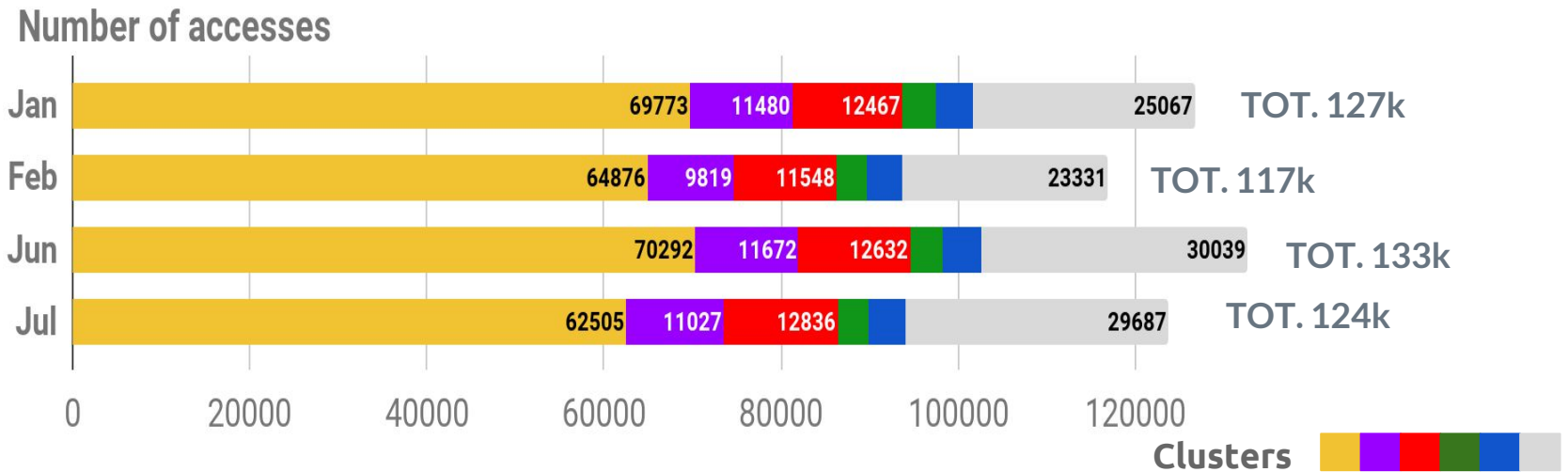
*EDs of a cluster are reachable from another one in less than 30'.*

12 EDs do not belong to any clusters: patients are always transported to the same ED.



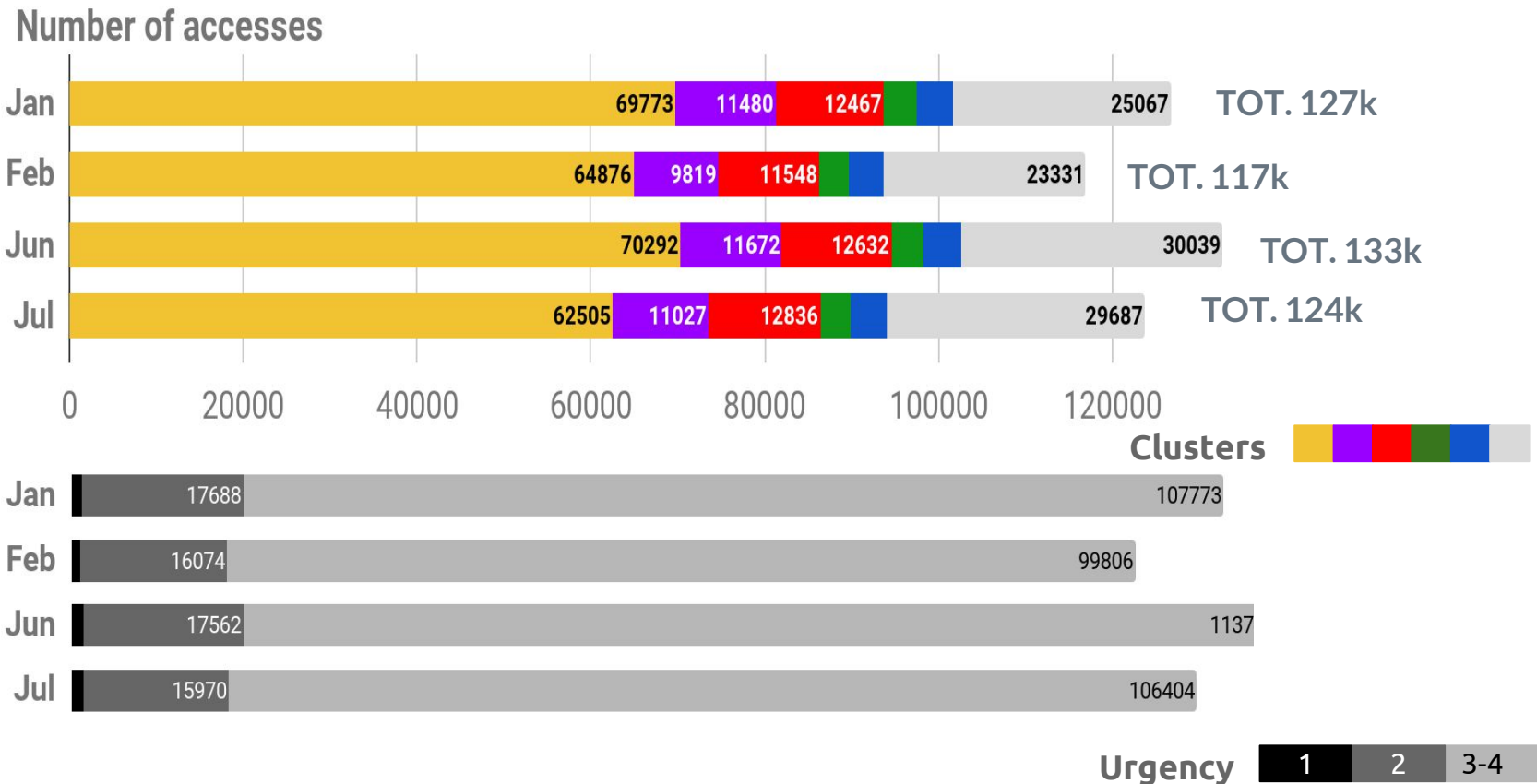
# Quantitative analysis - Scenarios

We present the quantitative analysis for 4 representative months in 2011.



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# Quantitative analysis - Results

Average **waiting time reduction** (minutes) over the **whole ED network** using the **policy  $P_1$**  instead of  $P_0$ . Results computed running the DES model 100 times (IID tests).

| % transported by EMS |            | 7%           | 12%          | 17%          | 22%          | 27%          |
|----------------------|------------|--------------|--------------|--------------|--------------|--------------|
| <i>January</i>       | <b>all</b> | <b>-15.5</b> | <b>-25.9</b> | <b>-34.7</b> | <b>-42.2</b> | <b>-50.8</b> |
|                      | EMS        | -17.8        | -21.6        | -24.7        | -27.8        | -34.4        |
|                      | others     | -15.4        | -26.7        | -37.0        | -46.6        | -57.4        |
| <i>February</i>      | <b>all</b> | <b>-6.3</b>  | <b>-13.2</b> | <b>-19.7</b> | <b>-26.3</b> | <b>-31.9</b> |
|                      | EMS        | <b>+4.3</b>  | +1.6         | -6.7         | -11.3        | -15.7        |
|                      | others     | 7.7          | -14.7        | -22.5        | -30.6        | -38.0        |

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| <i>June</i>          | <b>all</b> | <b>-19.7</b> | <b>-39.1</b> | <b>-64.5</b> | <b>-75.7</b> | <b>-80.8</b> |
|                      | EMS        | -5.8         | -19.9        | -45.5        | -58.9        | -66.4        |
|                      | others     | -20.8        | -41.8        | -68.5        | -80.6        | -86.3        |
| <i>July</i>          | <b>all</b> | <b>-8.3</b>  | <b>-13.2</b> | <b>-17.6</b> | <b>-22.2</b> | <b>-24.2</b> |
|                      | EMS        | <b>+3.9</b>  | <b>+2.6</b>  | -0.2         | -3.9         | -7.6         |
|                      | others     | -9.2         | -15.4        | -21.2        | -26.0        | -30.4        |



# Quantitative analysis - Results

Average **waiting time reduction** (minutes) over the **cluster  $C_1$**  using the **policy  $P_1$**  instead of  $P_0$ . Results computed running the DES model 100 times (IID tests).

| % transported by EMS |            | 7%          | 12%          | 17%          | 22%          | 27%         |
|----------------------|------------|-------------|--------------|--------------|--------------|-------------|
| <i>February</i>      | <b>all</b> | <b>+3.1</b> | <b>+1.1</b>  | <b>-1.6</b>  | <b>-4.6</b>  | <b>-6.6</b> |
|                      | EMS        | -6.5        | -5.4         | -5.1         | -5.9         | -7.3        |
|                      | others     | +9.6        | +9.8         | +8.3         | +6.4         | +4.8        |
| <i>July</i>          | <b>all</b> | <b>-8.4</b> | <b>-11.6</b> | <b>-12.0</b> | <b>-10.6</b> | <b>-8.9</b> |
|                      | EMS        | +0.8        | -6.2         | -9.5         | -9.9         | -9.5        |
|                      | others     | -12.6       | -17.0        | -18.1        | -17.2        | -15.9       |

# Conclusions

We presented a two-phase DES model to evaluate the dispatching policies for the regional network of EDs powered by HCBD.

The results showed the **effectiveness** of the proposed approach in terms of the capability of modelling a whole health care system through a DES approach, which exploits the availability of the HCBD.

Several interesting and counter-intuitive results have occurred through the quantitative analysis.

# What's next?

Future developments will be follow two main research lines:

- ▷ analysing other **dispatching policies**;
- ▷ improving the current model adding a more detailed representation of the **transportation network**;
- ▷ exploiting the demand prediction introducing **machine learning** within the modeling approach;
- ▷ extending such a modelling approach to a more complex **health care network** (to hospitals with their *specialties*).

Thanks!

**Any questions?**

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