Vehicular and Pedestrian Traffic: Optimization Through Digital Twins

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CALCOLO SCIENTIFICO E MODELLI MATEMATICI
ALLA RICERCA DELLE COSE NASCOSTE ATTRAVERSO LE COSE MANIFESTE
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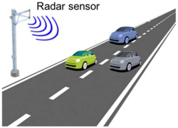
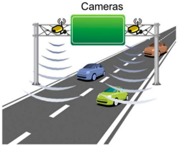
Plan

1. Collaboration no. 1: Autovie Venete
   - The A4 highway Trieste-Venezia
   - The multi-scale model
   - Results: TIPOT–model and TIPOT–alarms
2. Collaboration no. 2: Galleria Borghese
   - The museum
   - Tracking system
   - Data analysis and paths clustering
   - Digital twin
   - Results

Autovie Venete highway network





AV has video cameras, fixed and mobile sensors along the highway.

Collaboration

Goals

- Nowcasting and forecasting traffic flow on the highway, distinguishing light and heavy traffic. (**Google Maps is not enough!**)
- Analyzing sensor data in real-time and detect about critical situations.

Methods

- Differential models for nowcasting and forecasting
- Machine learning for data analysis

Main features of vehicular dynamics

Let us gather vehicles in two classes only: **light vehicles** (cars) and **heavy vehicles** (trucks, buses, etc.).

Lane usage

Heavy vehicles cannot use the fastest lane (the second or third one).

Creeping phenomenon

It can happen that heavy vehicles queue in the slow lane while light vehicles keep moving on the fast lane (at reduced speed).

Interactions among classes

Light and heavy vehicles must be considered separately, each class has its own dynamics.

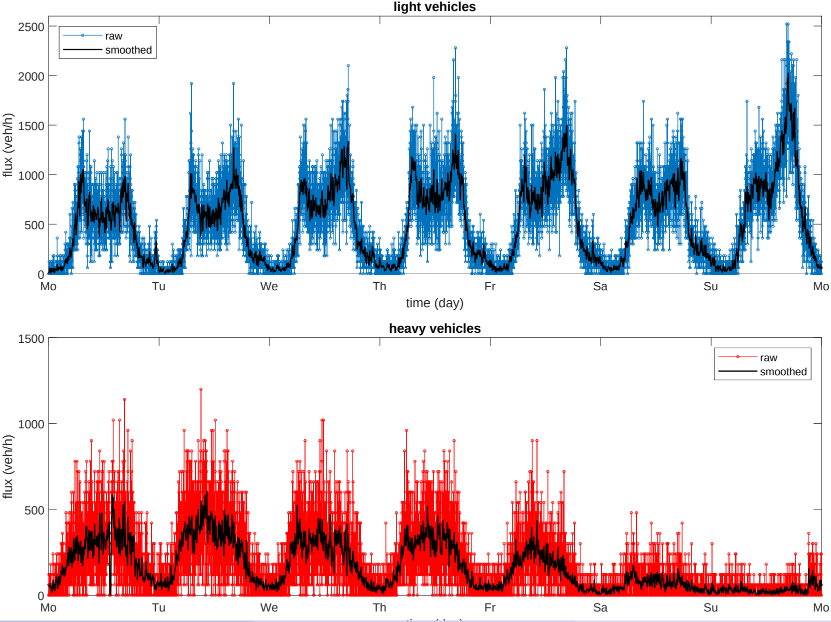
heavy $\longrightarrow$ light

Heavy vehicles always act as moving bottlenecks for light vehicles.
As the number of heavy vehicles increases, both maximal flux and maximal density of light vehicles decrease.

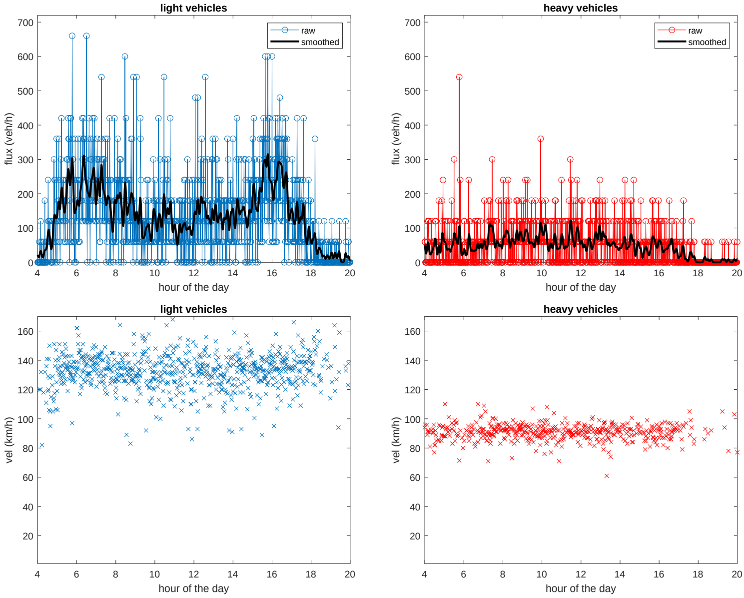
light $\longrightarrow$ heavy

Light vehicles modify the dynamics of heavy vehicles only when they have to invade the slow lane.
Heavy vehicles have to break because light vehicles place themselves in the space between two of them.

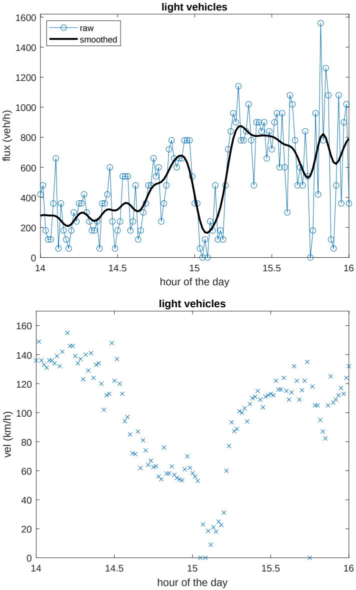
Weekly normal traffic



Daily normal traffic



Creeping



light vehicles
raw
smoothed
flux (veh/h)
hour of the day
heavy vehicles
raw
smoothed
flux (veh/h)
hour of the day
light vehicles
vel (km/h)
hour of the day
heavy vehicles
vel (km/h)
hour of the day

The multi-scale model

$\rho_{\rm H}(x,t)$	density heavy vehic	(veh/km)	$\rightarrow$ computed by $\{X_k\}_{k=1,\ldots,N}$.
$\rho_{\rm L}(x,t)$	density light vehic	(veh/km)	
$f_{\rm L}(x,t)$	flux light vehicles	(veh/h)	
X_k	pos heavy vehicle k	(km)	
V_k	vel heavy vehicle k	(km/h)	

The second-order microscopic model for heavy vehicles

$$\ddot{X}_k = A(X_k, X_{k+1}, V_k, V_{k+1}, \rho_{\rm L}), \qquad k = 1, \ldots, N-1$$

The $(k+1)$-th vehicle is always in front of the k-th one.
The first vehicle N has a separate dynamics.

The first-order macroscopic model for light vehicles

$$\partial_t \rho_{\rm L} + \partial_x f_{\rm L}(\rho_{\rm L}, \rho_{\rm H}) = 0, \qquad x \in \mathbb{R}, \quad t > 0$$

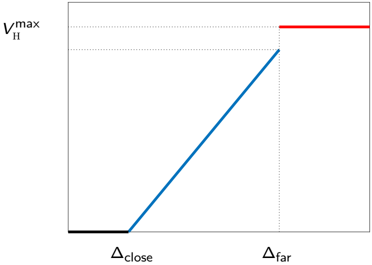
where $\rho_{\rm L} \rightarrow f_{\rm L}(\rho_{\rm L}, \rho_{\rm H})$ is called the *fundamental diagram*.

Microscopic model for heavy vehicles

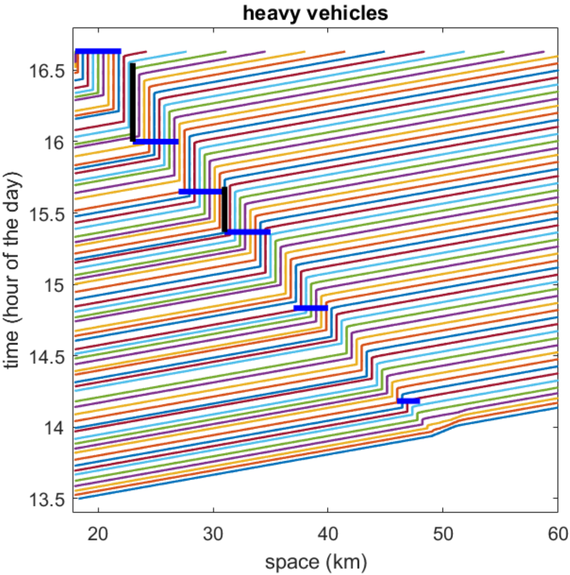
$$A\big(X_k, X_{k+1}, V_k, V_{k+1}\big) = \begin{cases} \frac{1}{\tau_{\text{acc}}}\Big(v^{\text{ZZ}}(\Delta_k) - V_k\Big), & \text{if } v^{\text{ZZ}}(\Delta_k) \geq V_k \\ \frac{1}{\tau_{\text{dec}}}\Big(v^{\text{ZZ}}(\Delta_k) - V_k\Big), & \text{if } v^{\text{ZZ}}(\Delta_k) < V_k \end{cases}$$

with $\Delta_k(t) := X_{k+1}(t) - X_k(t)$.

$$v^{\text{ZZ}}(\Delta) := \begin{cases} 0, & \text{if } \Delta \leq \Delta_{\text{close}}(\rho_{\text{L}}) \\ \frac{V_{\text{H}}^{\max}}{\Delta_{\text{far}}(\rho_{\text{L}}) - \Delta_{\text{close}}(\rho_{\text{L}})}(\Delta - \Delta_{\text{close}}(\rho_{\text{L}})), & \text{if } \Delta_{\text{close}}(\rho_{\text{L}}) < \Delta < \Delta_{\text{far}}(\rho_{\text{L}}) \\ V_{\text{H}}^{\max}, & \text{if } \Delta \geq \Delta_{\text{far}} \end{cases}$$

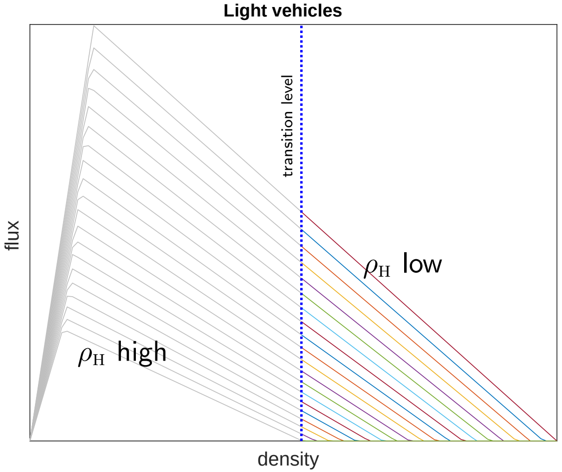


A single stop & go wave

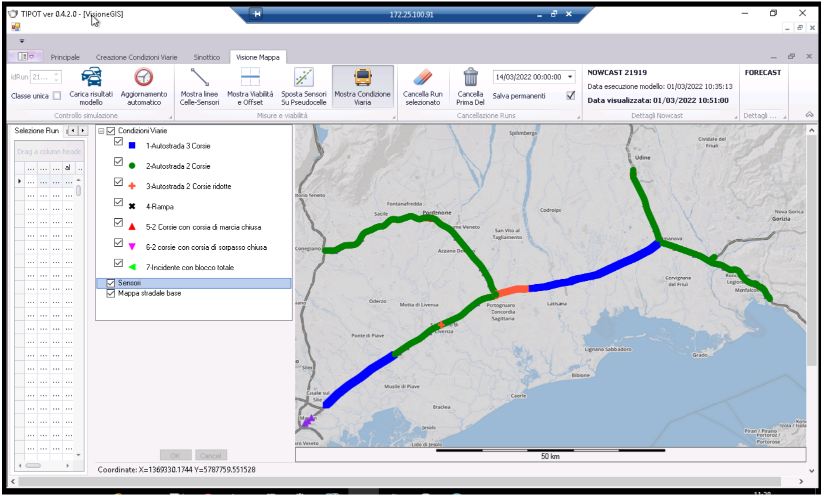


Macroscopic model for light vehicles - Fundam. diagram

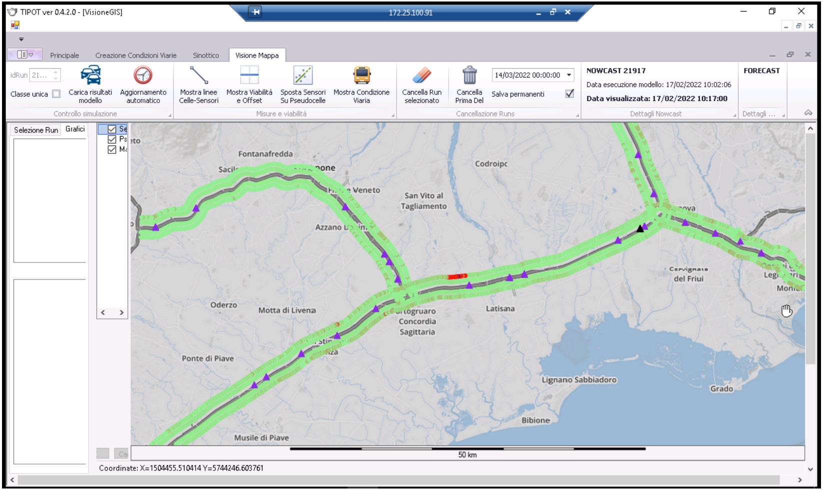
$$\rho_{\mathrm{L}} \to f_{\mathrm{L}}(\rho_{\mathrm{L}}, \rho_{\mathrm{H}})$$



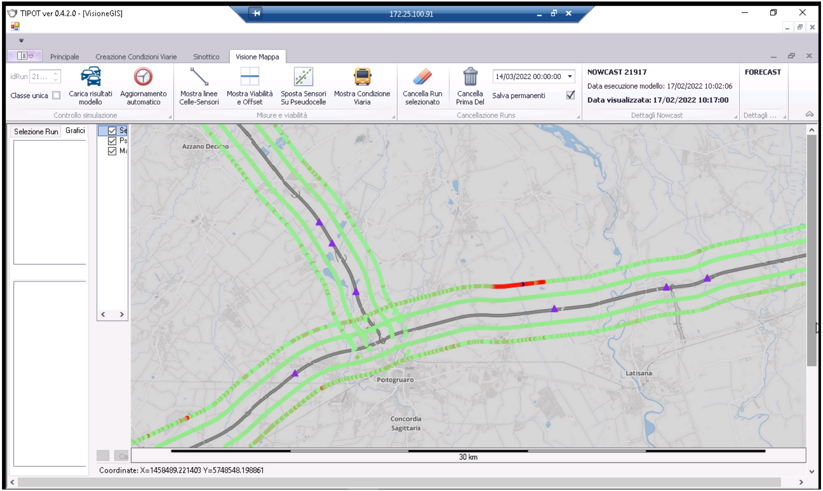
TIPOT–model: road conditions



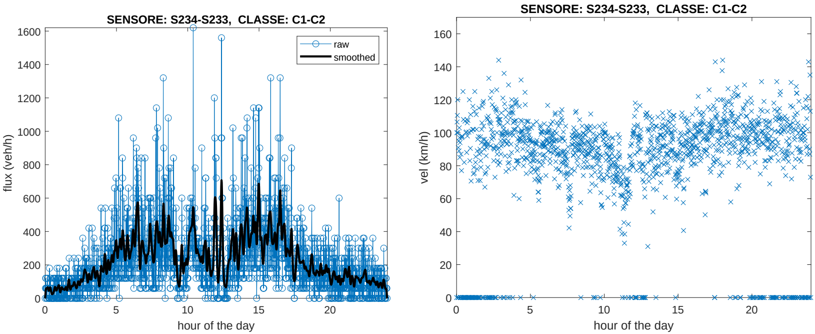
TIPOT–model: densities



TIPOT–model: densities



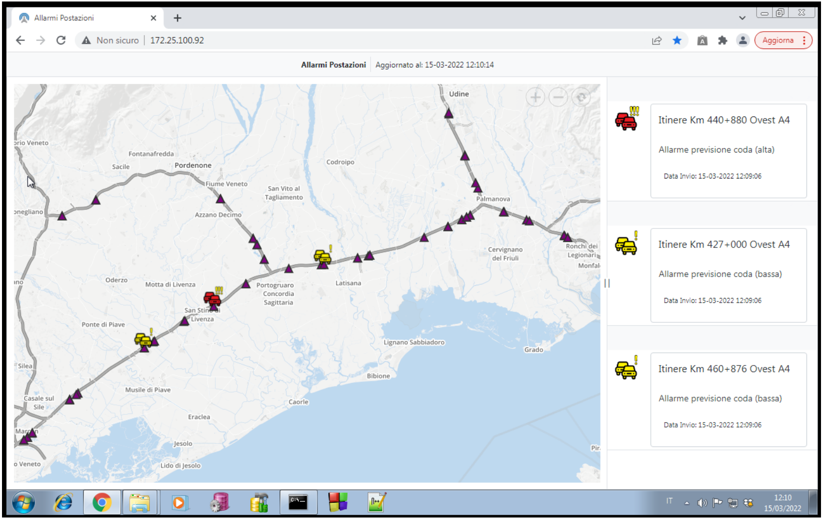
TIPOT–alarms



Real-time analysis of sensors data (flux & velocity) for

- detect congestion [Machine Learning]
- forecast congestion [Machine Learning]
- detect large flux
- detect sensor failure

TIPOT–alarms



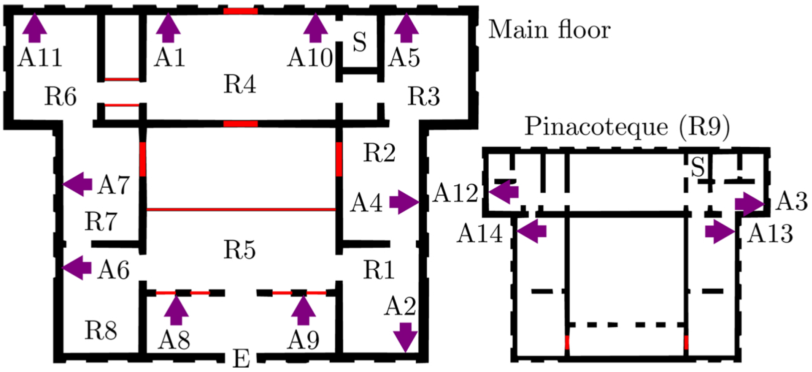
Plan

Collaboration #2: Galleria Borghese

The museum

- The world-renowned Galleria Borghese museum is a relatively small, two-floor museum with **three entrances** and 21 exhibition areas.
- Museum curators established to **schedule the visits**: tickets had to be booked in advance and gave access to the museum for a slot of 2h, five slots per day, 360 visitors per slot.

Map of the museum



Rooms are numbered but there is no predefined or suggested path.
It was not clear how visitors move inside the museum.

Collaboration #2: Galleria Borghese

Goals

Measure, **understand**, **model**, and **optimize** the visitors flow under the numerous constraints, using in the optimal way the three entrances.

Methods

- Manual counting for Eulerian tracking systems
- Beacon BLE for Lagrangian tracking systems
- Machine learning for path reconstruction
- Clustering techniques for most common paths and anomaly detection
- Markov chains with memory for the digital twin
- Brute force attack for optimization

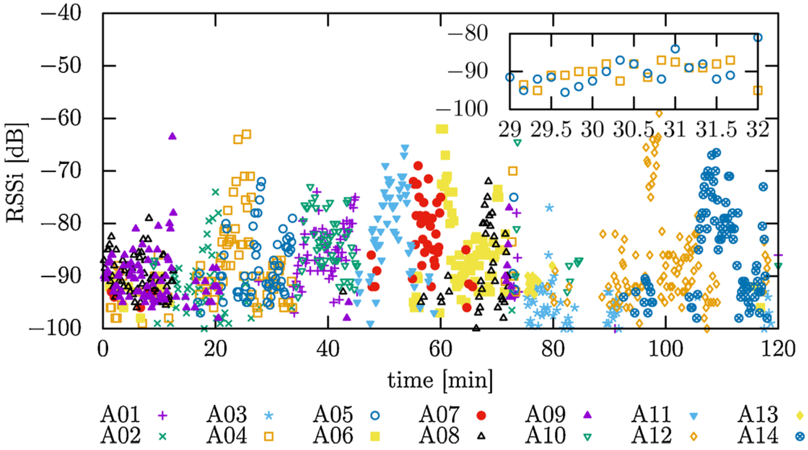
Lagrangian tracking systems

Tracking systems

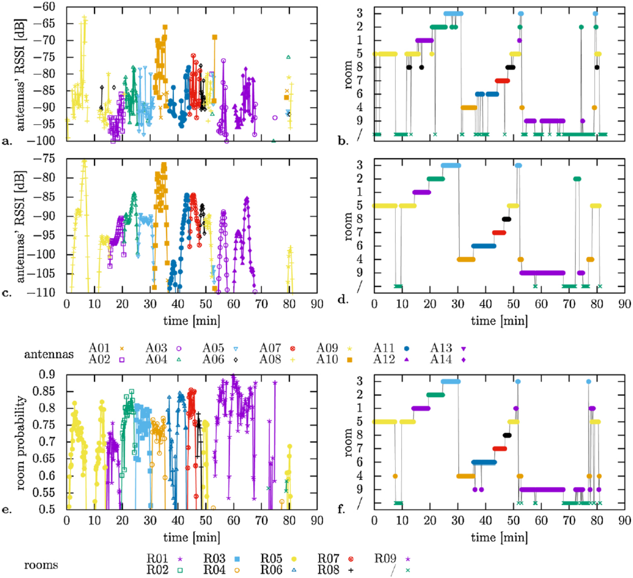
We used **beacon BLE** as transmitters and **Raspberry Pi**'s as receiving antennas. RPi's can be powered by portable power banks.

Other methods: RFID, beacon Bluetooth, video cameras, 3D thermo- or laser-scanners

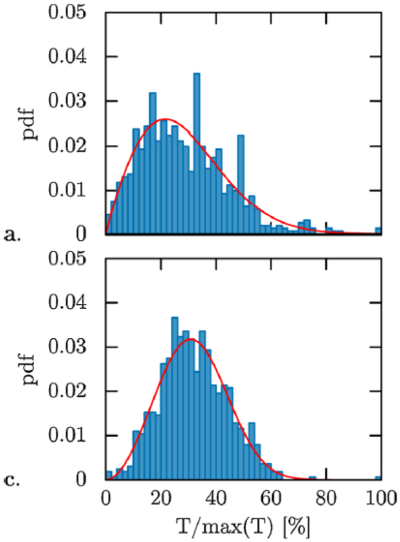
Raw data


−40
−50
−60
−70
−80
−90
−100
RSSi [dB]
0
20
40
60
80
100
120
time [min]
−80
−90
−100
29
29.5
30
30.5
31
31.5
32
A01
A02
A03
A04
A05
A06
A07
A08
A09
A10
A11
A12
A13
A14

Trajectory reconstruction

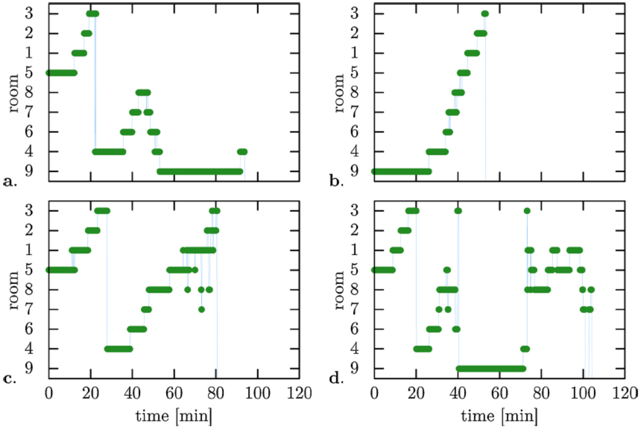


Statistics: time of permanence



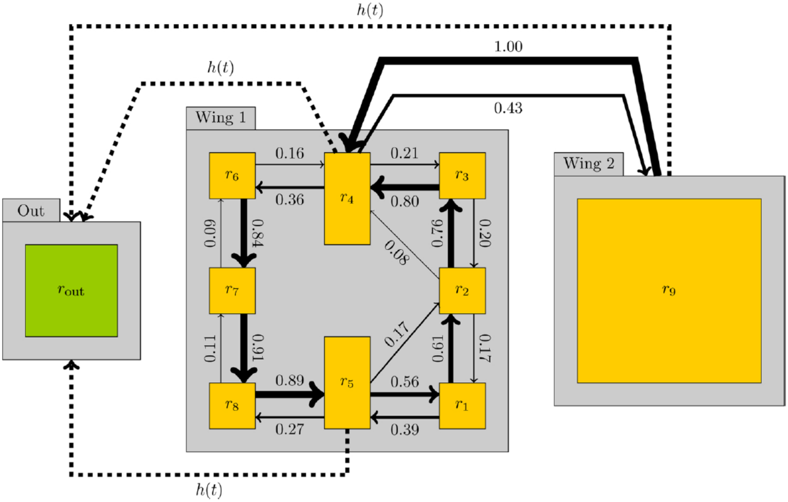
Trajectory clustering

Clusters are obtained by an agglomerative hierarchical clustering (AHC) technique. It considers a bottom-up cluster tree (dendrogram), that, step by step, gathers trajectories according to their mutual likelihood.

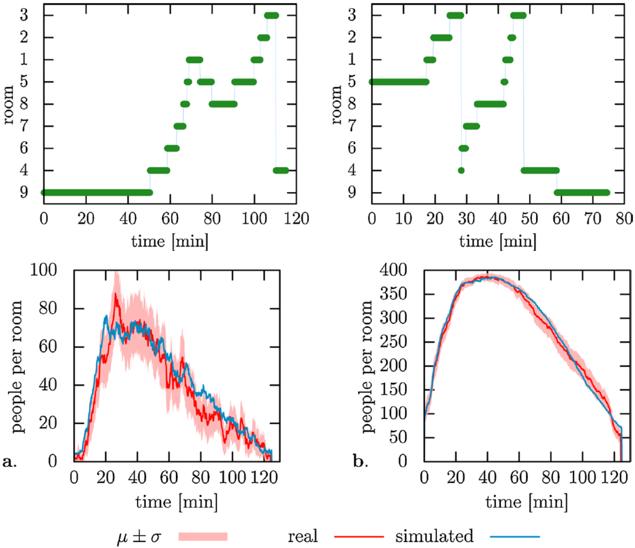


Four representative trajectories (centroids) of clusters joining respectively a. 16%, b. 9%, c. 4%, d. 1% of the trajectory data set. Representative trajectories may show spikes (see, e.g., c., ~75 min). According to (10), this phenomenon arises whenever rooms have approximately the same number of visitors within the same interval of time.

Digital twin



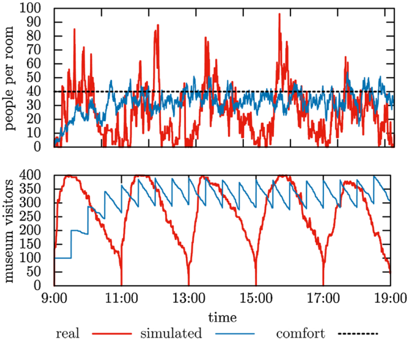
Digital twin: simulated trajectories vs. Eulerian measurements



Optimization

We tried different configurations varying the **time of entrance**, the **duration of the slots**, the **number of people of each slot** and the **percentage of visitors entering from each entrance**.

This is the result with 100 people entering every 30 minutes from rooms 1 and 4, with no time limit



Real-life implementation

Following this study, in September 2021 the curators decided to change the management of the flows of visitors.

Now 180 visitors enter every hour for a visit lasting 2h (but without forced exit). The overlapping of turns has brought obvious advantages, allowing to sell about 15% more day tickets with the same overcrowding or, similarly, to reduce overcrowding in the Pinacoteca by 15% for the same number of tickets sold.

As for the entrances, it has not yet been possible to reach the optimum due to restrictions COVID-19.

Main references

- M. Briani, E. Cristiani, P. Ranut, *Macroscopic and multi-scale models for multi-class vehicular dynamics with uneven space occupancy: a case study*, Axioms, 10 (2021), 102.

- P. Centorrino, A. Corbetta, E. Cristiani, E. Onofri, *Managing crowded museums: Visitors flow measurement, analysis, modeling, and optimization*, Journal of Computational Science, 53 (2021), 101357. (open access)