From Data to Digital Twin for Smart Mobility

Course for the PhD program Information Engineering
2023-2024

Lesson #3

Environmental applications for TFR

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Environmental applications for TFR

FROM DATA TO DIGITAL TWIN
FOR SMART MOBILITY

Introduction

- The focus on environmental issues has become increasingly relevant for smart city and mobility managers.
- There is evidence that exceeding the limits of certain pollutants leads to serious health problems for citizens in both short and long terms.
- For this reason, data analytics approaches are devoted to air pollution analysis.

Introduction

Recently, there is a deeper understanding of the environmental parameters:

- PM10 (Particulate Matter), PM2.5,
- CO (Carbon Monoxide), **CO_2** (Carbon dioxide),
- SO_2 (Sulfur dioxide),
- O_3 (Ozone),
- H_2S (Hydrogen Sulfide),
- NO (nitric oxide), NO_2 (Nitric dioxide), NO_x (Nitric monoxide and dioxide)).

Introduction

The most common issues are:

- How much the pollutants are influenced by the city’s structures.
- What are the reasons for the registered high values from IOT Data Network.
- What is the dynamic of their diffusion and propagation.

Introduction

- Greenhouse Gas (GHG) emissions make a relevant contribution to the climate changes and global warming.

- In the mobility context, **CO2** emissions from burning fossil fuel represent the primary contribution in the transportation field.

- Traffic emissions from fuel combusted in vehicles are typically estimated by **emission factors** (EFs)

Introduction

- The emission factor is the emission rate of a given pollutant relative to the intensity of a specific activity.

In the context of mobility:

- The **distance travelled** by a vehicle has a large influence on emissions, since in general a greater activity (greater distance) gives greater emissions.

- **Vehicle speed** and **Travel time** have important influence on emissions.

Introduction

- Emissions depend on **vehicle category** also. Different vehicle categories have different EFs due to factors such as vehicle mass, fuel specification, engine size, aerodynamics, and emissions control technology.

- Summarizing, almost all **CO2 emissions in vehicular traffic** depend on a variety of vehicle and traffic related parameters, such as vehicle characteristics and motorization, **driving behaviour** and **traffic conditions.**

Goal

We present a model to estimate the CO_2 emissions from traffic flow data, characterising the specific (city) traffic flow in terms of emission factors which is regarded as the amount of CO_2 produced per vehicle for unit distance [gCO2/Km per car], in order to:

- Identify the function/relationship from traffic flow to CO_2.
- Estimate the total CO_2 production of the city by Traffic Flow Reconstruction (TFR).

Goal

- Determine the emission factors taking into account **different traffic behaviours** from fluid traffic to “stop-and-go” conditions (**congested and uncongested traffic** situations).
- Consider the changes of the emission factor in **different periods** of the year.
- **Validate the precision** of the (obtained) indirect estimation of CO2 on the basis of traffic flow.
- **Reconstruct** CO2 emissions in different areas by TFR.

Data (and related problem) description

- Both **air quality** sensors and **vehicular traffic** sensors are taken into account for the present study, considering alignment problems in spatial and temporal terms.

- Typically, CO2 measures are performed either by the count of its particles in the air (commonly, part per million, ppm) or by means of the CO2 weight in a given air volume (mg/m^3 or g/m^3), for some certain temporal windows in a given location.

- In any city, the number of CO2 sensors is limited. For example, in the municipality of Florence about **10 sensors** are present.

Data (and related problem) description

- Those sensors are not all in critical locations for the traffic neither for pollutant.
- SMART28 and SMART29 are in dense traffic roads.
- SMAR27 and SMART09 are in mid-range traffic areas.
- For each air quality sensor, the data are registered every 2 minutes.

Data (and related problem) description

- The data exploited refers to (about) 50 traffic flow devices located in the selected area.
- All of them are well calibrated and produce coherent results (different calibration).
- Typically, traffic sensors data are simultaneously registered every 10 minutes.

Data (and related problem) description

- Analysing their geo-distribution, it can be observed that CO2 sensor locations have one or more traffic sensors in their proximity, while they are not precisely co-located.

- The actual traffic in the CO2 sensor position can be estimated by **traffic flow reconstruction**.

- The traffic flow measures strongly dependent on a number of road features: road relevance (primary, secondary, etc.), number lanes, speed limits, monitored distance, etc.

Traffic sensors

Traffic flow sensors provide at each time slot different measures regarding vehicular traffic, such as:

- **vehicular traffic flow**: number of vehicles crossing the supervised location during a given period of time (which is usually referred to the hour, that is, #cars/h);
- **vehicular average speed**: average speed of the vehicles crossing the supervised location (measured in km/h);
- **vehicular density**: number of vehicles in terms of road occupancy (measured in #cars/km).
- **travel time**: average time that vehicles take to transit the supervised area (reported in s).

Traffic sensors

- Each traffic sensor data may present **a specific behaviour** depending on the context of installation.

- At each traffic sensor location, the measured vehicular traffic flow (density) depends on the number of lanes of the road where the traffic sensor is placed.

- In general, the measured vehicular traffic flow (density) coming from a traffic sensor located in a multiple lane road is greater with respect to the traffic flow (density) value coming from a single lane road.

Traffic sensors

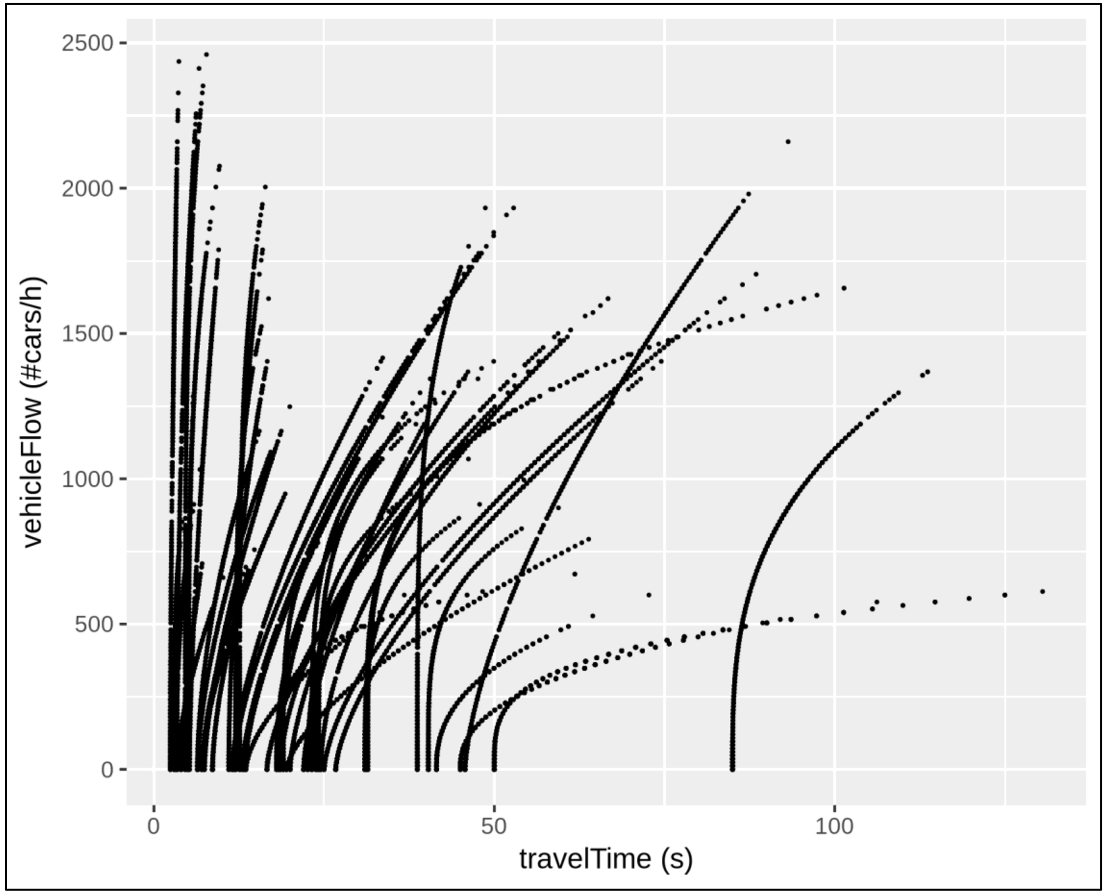
- The traffic sensors often consist of optical cameras and the related measured data depends on some specific parameters that are set up on the traffic sensor itself, that is, the selected area to be monitored and the length of the observed road segment.
- For example, when a traffic sensor is located in a long straight road, then it is set up in order to monitor a long road segment.
- While, when the traffic sensor is placed in proximity of a road curve or a road junction, then the supervised area is smaller.

Traffic sensors

- Each traffic sensor monitors a fixed supervised area which is constituted by means of a given road segment length. Then, each traffic sensor admits specific travel time measurements.

- In absence of traffic congestion at the traffic sensor locations, the measured travel time (to across the segment) is higher when the related monitored area is greater/longer, since the vehicles need of a more time to travel.

Traffic data



The collection of monitored traffic data coming from about 50 traffic sensors at sparse locations in the network, in 7 days observation.

Each traffic sensor location presents a specific traffic behavior depending on the travel time.

Traffic data

- In absence of traffic congestion, each traffic sensor admits a **minimal** (monitored) travel time which can be defined as the vehicular time needed to across the supervised area within (at most) the speed limit occurring at the related traffic sensor location.

- Thus, different minimal across/travel time can be registered for different traffic sensors.

Traffic data normalization

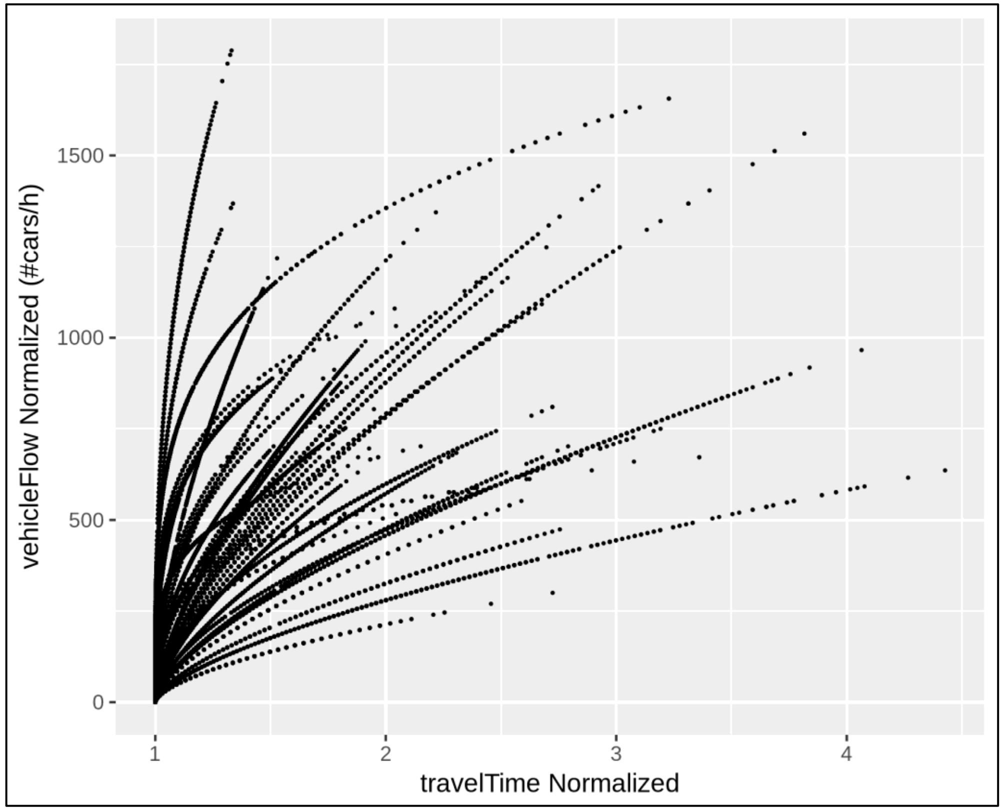
The following normalization approach is conducted for each i-th traffic sensor:

- measured vehicular traffic flow, denoted by $F(t)$ at a given timestamp t, is normalized with respect to the number of lanes, denoted by C, of the road of the location. Thus, the normalized vehicular traffic flow at a given timestamp t, denoted by $Fn(t)$, is given by $Fn(t) = F(t)/C$;

- measured travel time, denoted by $T(t)$ at a given timestamp t, is normalized with respect to the *minimal travel time*, denoted by Tm, occurring in the absence of congestion in the sensor location. Tm can be defined as the travel time needed to across the area at speed limit of the observed segment. Thus, the normalized travel time at a given timestamp t, denoted by $m(t)$, is given by $m(t) = T(t)/Tm$

Traffic data normalization

- Then, all the curves starts from the origin and the data are aligned



The **normalized travel time** is a dimensionless value, denoted by *m*, and it can be considered as a multiplier factor of a given minimal travel time.

So that, we set m=1 in absence of traffic congestion for each traffic sensor location and the related traffic data can be comparable.

Traffic data normalization

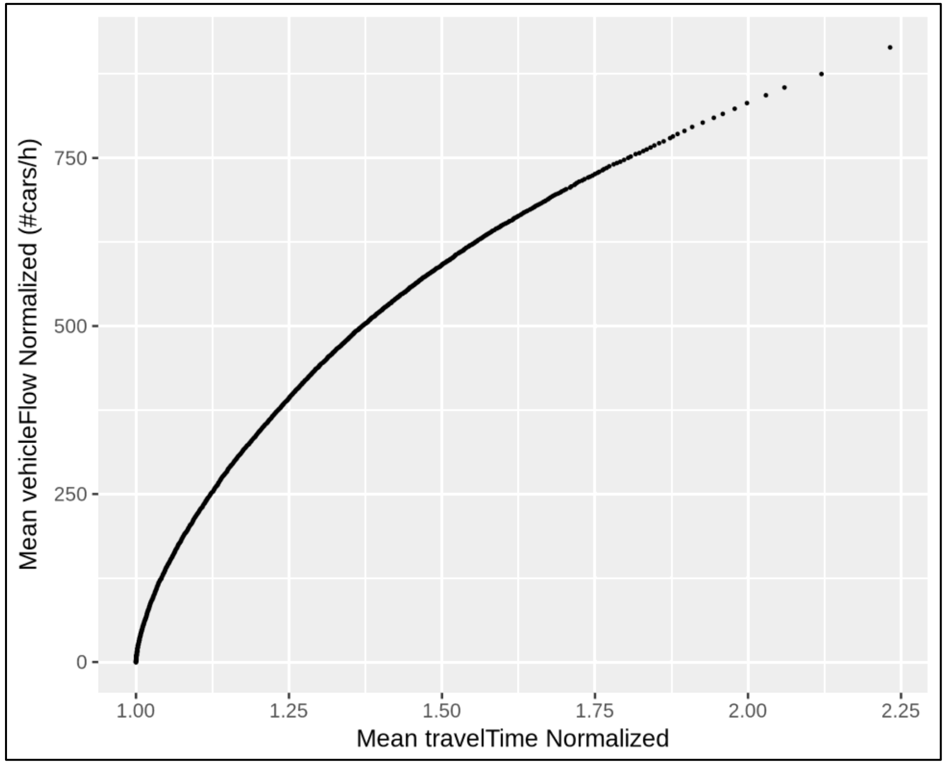
- The normalized measures are represented by means of the same point/contribution in the traffic data alignment:

For example:

- S1: 2 lanes, 0.35 km, 50 Km/h speed limit, 25.2 s minimal travel time;
- S2: 1 lane, 0.25 km, 30 km/h speed limit, 30 s minimal travel time.
- At a given time, the sensor located in the former monitored road segment registers 800 vehicles/h and the related travel time is 37.8 s. The sensor in the latter monitored road segment registers 400 vehicles/h and the related travel time is 45 s.
- Normalization: 400 vehicles/h cross the single line street in 1.5 times their minimal travel times, respectively. Then, the measures are now aligned and comparable.

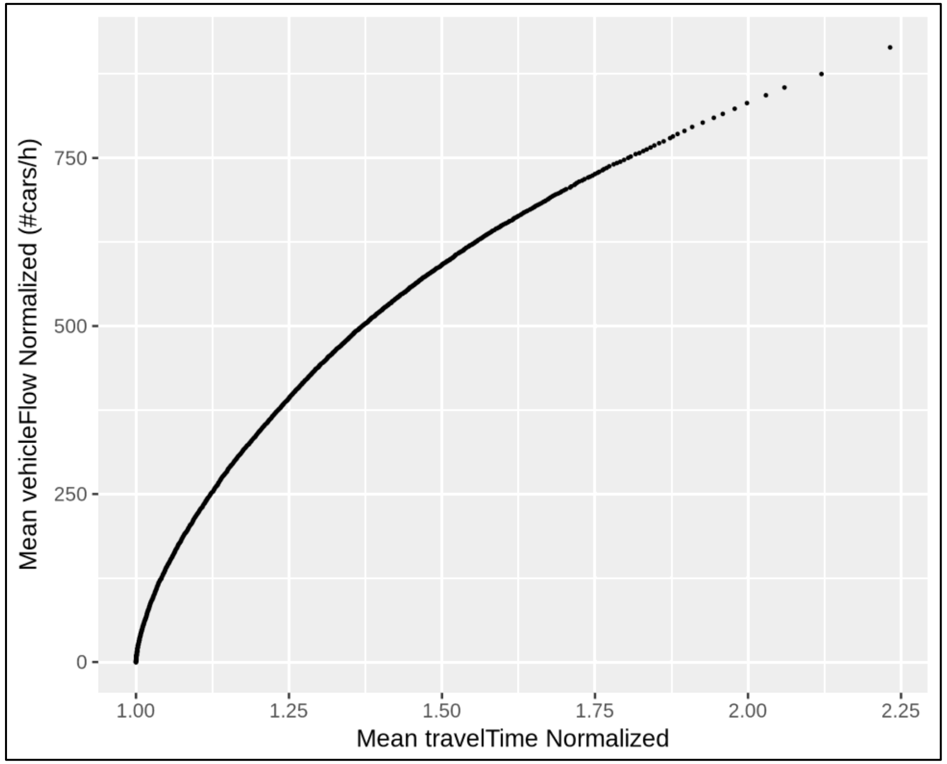
Average Traffic Trend

- An average traffic flow value can be estimated with respect to the corresponding average travel time in the network



Average Traffic Trend

- An average traffic flow value can be estimated with respect to the corresponding average travel time in the network



Let start to study the traffic conditions by considering the described mean traffic behaviour in order to observe **uncongested and congested** traffic situations (via changing modality).

Understanding

- The vehicular traffic flow and travel time data are largely influenced by congested traffic conditions.
- Congested traffic situations are in presence of a higher vehicular traffic flow in the monitored road section.
- The travel time depends on the vehicular average speed which is getting closed to 0 when traffic congestion occurs (a higher travel time reduces the vehicular flow).

Flow Rate

- The uncongested and congested traffic situations are implicitly determined by means of the volume of vehicular flow which passes the supervised area in the unit of time.

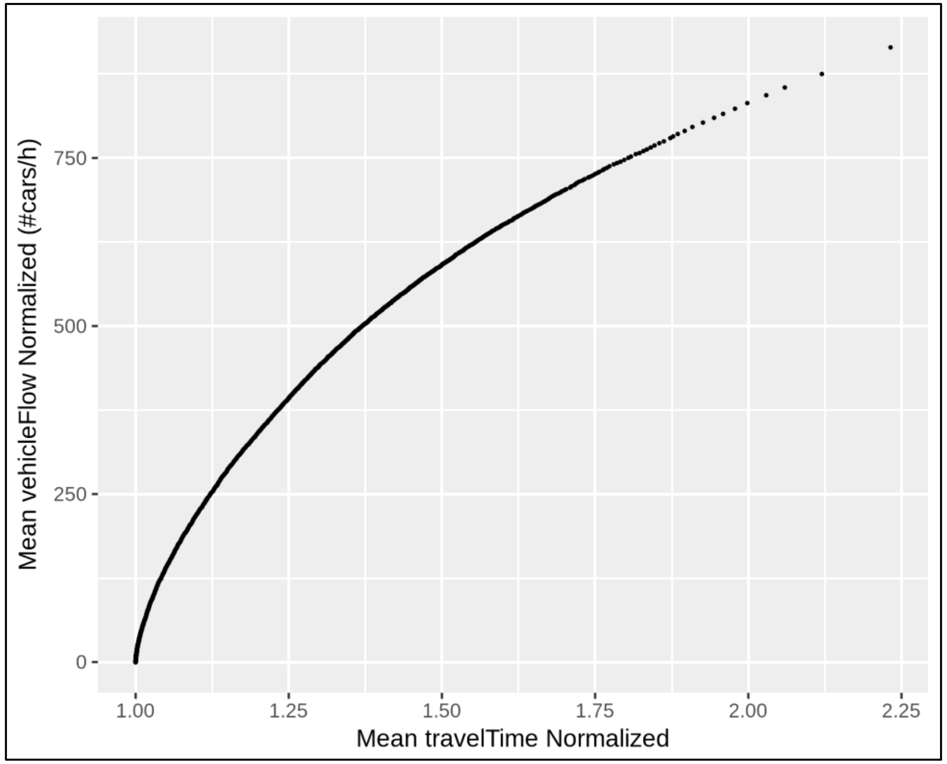
- The vehicular *Flow Rate* at time *t*, can be defined as follows:

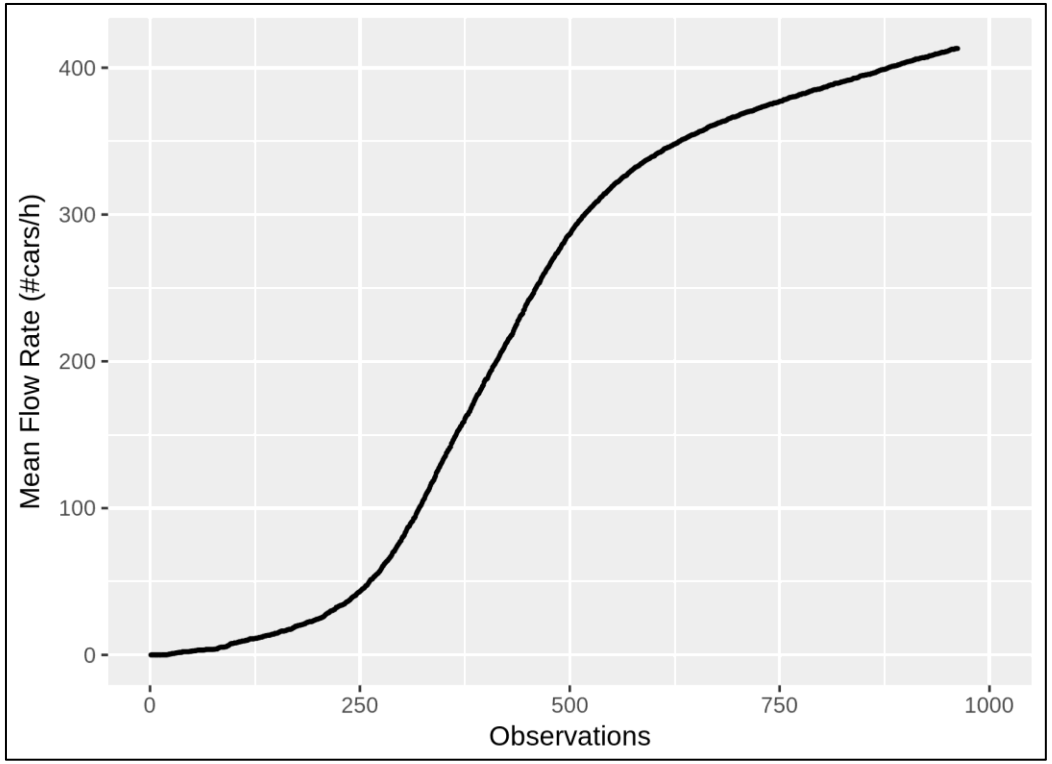
$$FR(t) = \frac{Fn(t)}{m(t)}$$

- In Fluid dynamics: the volume of a fluid passing in the time unit.

Flow Rate

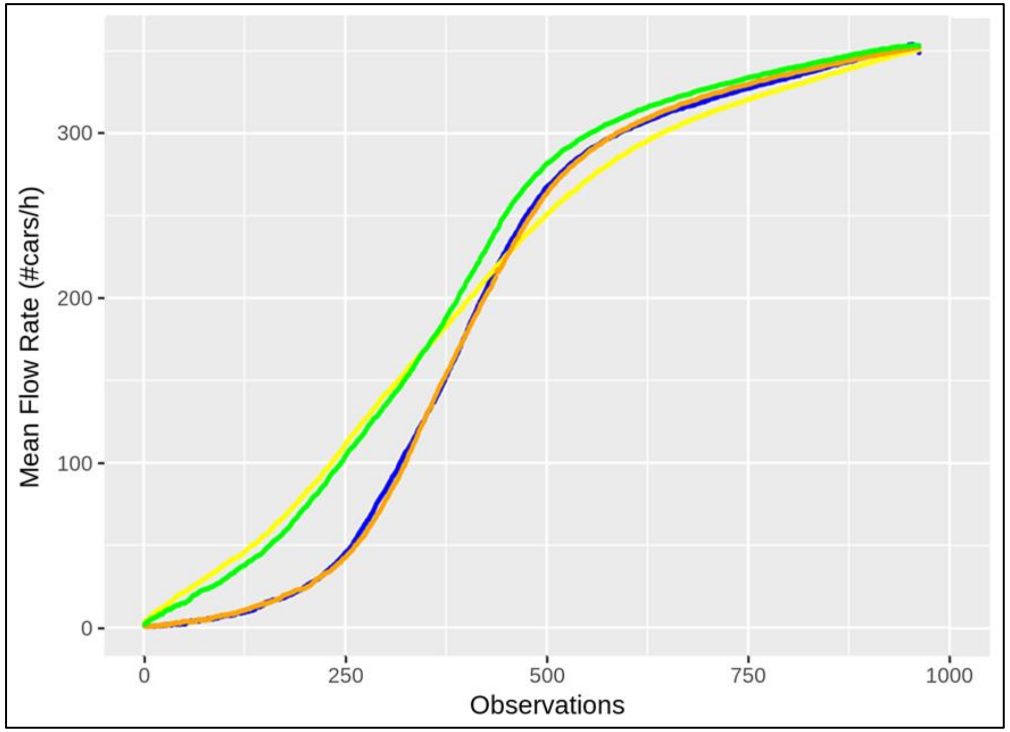
The general behaviour of the Mean Flow Rate, MFR (where the observations are sorted according to increasing travel time measurements in the whole network).





Flow Rate

- The flow rate can be also computed through the data coming from a single traffic sensor, or different periods of time, etc.

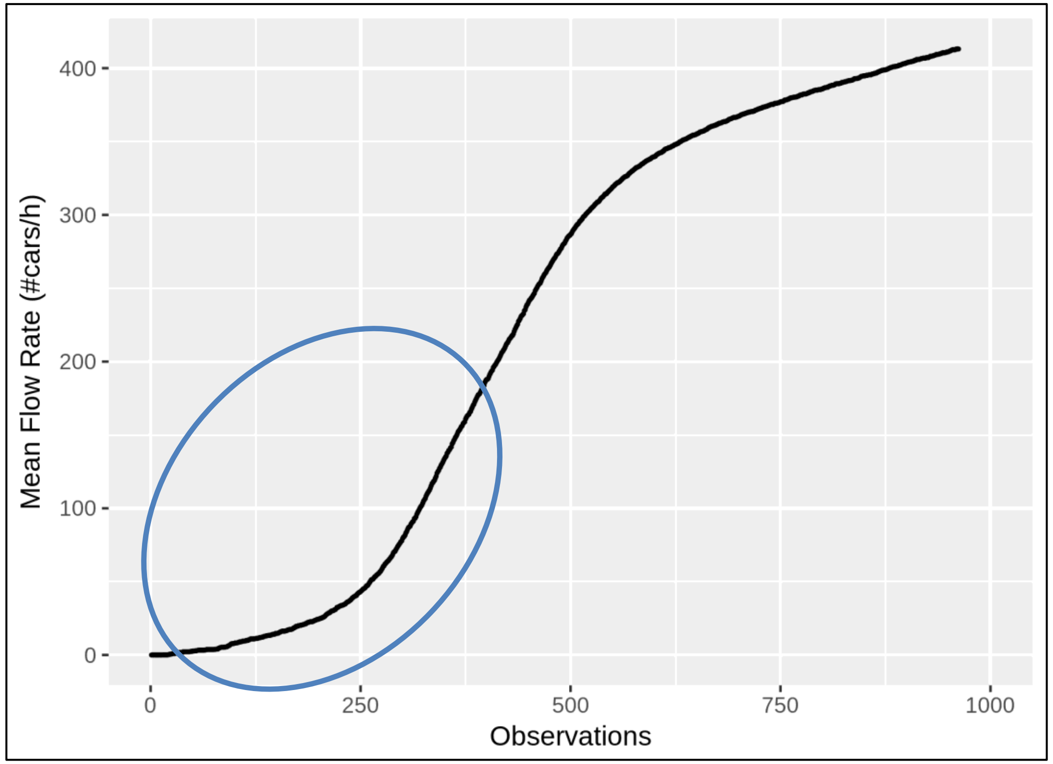


The **seasonal changing** curves are shown in terms of MFR, where the behaviours of the seasons are depicted in blue (March), green (May), yellow (July) and orange (October).

Traffic Flow Modalities: congested and uncongested

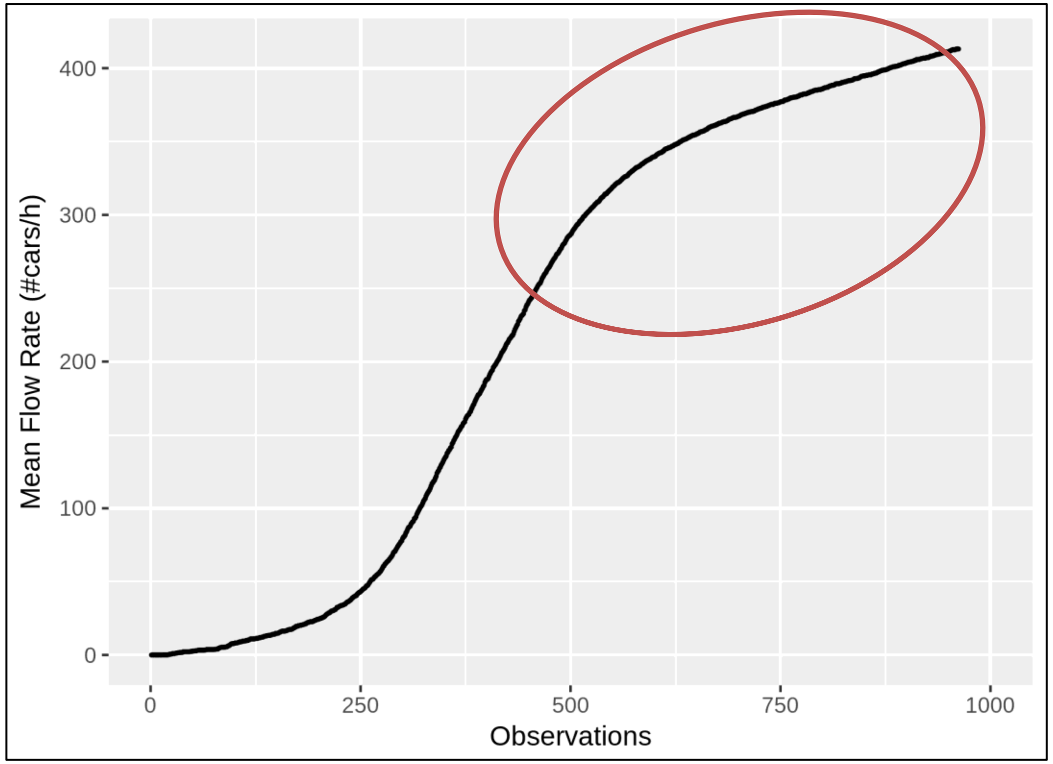
- *Formal Approach* via Flow Rate (MFR).
- 2 distinct situations in the FR diagrams are identified in terms of (*chancing*) **concavity**.

Traffic Flow Modalities: congested and uncongested



When the concavity of the flow rate is **upwards**, the vehicles passage assumes a quickly increasement and the traffic flow proceeds unimpeded. Then, situation of **uncongested** traffic is assumed.

Traffic Flow Modalities: congested and uncongested



When the concavity of the flow rate is **downwards**, vehicles passage assumes a reduction up to a quasi-constant condition. Such a traffic modality occurs when the flow is slowed down and **stop-and-go** situations arise since the road capability is limited.

Traffic Flow Modalities: congested and uncongested

- There exists an *inflection point* in which FR curve changes concavity: in that point the travel time starts to decrease, and the traffic starts to congest.

- Such a concavity changing in each diagram can be determined by means of the unique inflection point.

Polynomial Approximation

- Function $\boldsymbol{f}$ analysis defining FR behaviour.
- In order to identify function $\boldsymbol{f}$, we proceed performing a polynomial approximation to minimize the worst-case error.
- Thus, the polynomial approximation $\boldsymbol{P}$ of function $\boldsymbol{f}$ minimizes $|\boldsymbol{P}(\boldsymbol{x}) - \boldsymbol{f}(\boldsymbol{x})|$ where $\boldsymbol{x}$ varies over the chosen interval.
- Therefore, approximation $\boldsymbol{P}$ of function $\boldsymbol{f}$ has been obtained by using a third order polynomial form: $\boldsymbol{P}(\boldsymbol{x}) = \boldsymbol{a}\boldsymbol{x}^{\boldsymbol{3}} + \boldsymbol{b}\boldsymbol{x}^{\boldsymbol{2}} + \boldsymbol{c}\boldsymbol{x} + \boldsymbol{d}$.
- Different values of the coefficients $(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}, \boldsymbol{d})$ of $\boldsymbol{P}$ determine a different traffic behaviour in term of FR

Polynomial Approximation

- An example of the coefficients related to the polynomial approximations of the *MFR(Spring)* and *FR(Spring,i)* for 3 traffic flow sensors during the (same) selected period of time in spring.

Polynomial Approx.	a	b	c	d
MFR(Spring)	−0.0000011	0.0014465	0.0686048	−17.38807
FR(Spring,1)	−0.0000019	0.0027314	−0.140624	−9.454277
FR(Spring,2)	−0.000001	0.0016093	−0.247455	2.96993
FR(Spring,3)	−0.0000019	0.002776	−0.471167	11.87328

Inflection Point

- Since the polynomial approximation $\boldsymbol{P}$ is differentiability class $\boldsymbol{C^2}$ for each set of finite coefficients differ from zero ($\boldsymbol{P}$, its first derivative $\boldsymbol{P'}$, and its second derivative $\boldsymbol{P''}$, exist and are continuous), then the condition $\boldsymbol{P''} = \boldsymbol{0}$ can be used to find the desired inflection point in the considered interval of vehicular traffic behaviour.

Traffic Flow Sensors	Inflection Point (T-TH OBS) on P	Flow Rate (#Cars/h)	Traffic Flow (#Cars/h)	Traffic Density (#Cars/Km)
All city sensors	438	215.8	255	7.24
S1 (near SMART27)	479	366	366.88	7.12
S2 (near SMART28)	536	186.14	216	6.35
S3 (near SMART29)	487	234.24	240	4.21

Model

How do the traffic uncongested and congested situations contribute to CO2?

- The CO2 measured by sensor is related to the surrounding area of the sensor.
- The idea is to consider the traffic amount contained in the road segments in which the CO2 sensors are located.
- From the total number of the reconstructed road segments by TFR, choosing the closest one to each air quality sensor.
- The computation of CO2 depends on the traffic flow and the emission factors which are different for congested and uncongested traffic flow cases.

Model

From *traffic flow* to *CO2*

- In order to related the amount of CO2 in a given road segment with the traffic in its proximity, it is necessary to associate the CO2 measurement with a volumetric section of road segment. Let *t* be the time interval and *z* be the CO2 sensor ID, we have:

$$S(z)G(t,z) = K_1(z)F_1(t,z)L(z) + K_2(z)\ F_2(t,z)L(z)$$

Model

$$S(z)G(t,z) = K_1(z)F_1(t,z)L(z) + K_2(z)\ F_2(t,z)L(z)$$

$S(z)G(t,z)$ is the amount of gCO_2 in a volumetric section of the road segment at a given time t, where:

- $G(t,z)$ is the measurement of CO_2 from the sensor in gCO_2/m^3 in the time interval (these values are measured by the CO_2 sensors);
- $S(z)$ is the area in which the sensor collects the values in m^3 and it is estimated on the road segments close to the CO_2 sensor location. More precisely, we have:

$$S(z) = L(z)\ C(z)\ W(z)\ H(z)$$

where $C(z)$ is the number of lanes, $W(z)$ is the width of the road lane, and $H(z)$ is the height of the volume, which depends on the position of the CO_2 sensor (typically at 3 m).

- $L(z)$ is the road length corresponding to the amount of m or Km performed by the vehicles in that specific area of the CO_2 sensor, supposing that the vehicles change neither road nor behaviour in the segment.

Model

$$S(z)G(t,z) = K_1(z)F_1(t,z)L(z) + K_2(z)\ F_2(t,z)L(z)$$

- Contribution coming from vehicles/cars moving in uncongested conditions:
  - $F_1(t,z)$ is the traffic count in uncongested conditions in terms of #cars in the time interval. This can be measured on the basis of traffic sensors and/or estimated as solutions of the above-presented LWR PDE via the traffic reconstruction model
  - $K_1(z)$ is an emissions factor to be determined, which is the amount of gCO_2/km per car in uncongested conditions.

Model

$$S(z)G(t,z) = K_1(z)F_1(t,z)L(z) + K_2(z)\ F_2(t,z)L(z)$$

- Contribution coming from vehicles/cars moving in congested conditions:
  - $F_2(t,z)$ is the traffic count in congested conditions in terms of #cars in the time interval. This can be measured on the basis of traffic sensors and/or estimated as solutions of the above-presented LWR PDE via the traffic reconstruction model);
  - $K_2(z)$ is an emissions factor to be determined, which is the amount of gCO_2/km per car in congested conditions.

Model

$$\boxed{F_1(t,z) = D_1(t,z)\, V_1(z)}$$

$$\boxed{F_2(t,z) = D_2(t,z)\, V_2(z)}$$

$V_1(z)$ and $V_2(z)$ are the average vehicular speeds in z-th location in the cases of uncongested and congested situations, respectively

- $\boxed{\text{If } \frac{\rho(t,z)}{C(z)} \leq q(z), \text{ then } D_1(t,z) = \rho(t,z) \text{ and } D_2(t,z) = 0;}$
- $\boxed{\text{If } \frac{\rho(t,z)}{C(z)} > q(z), \text{ then } D_1(t,z) = 0 \text{ and } D_2(t,z) = \rho(t,z).}$

$\rho(t,z)$ is the traffic density (#cars/km)

$q(z)$ is the value on the inflection point of traffic density in the proximity of the z-th air-quality sensor location to detect congested and uncongested cases,

$C(z)$ is the number of road lanes;

Model

- It is possible to estimate the unknowns $K_1(z)$, $K_2(z)$ for each location in which CO2 and traffic flow data are known.

- The estimation can be performed by means of a *multilinear regression* in which the dependent variable is the amount of $gCO2$ in a volumetric section of the road segment, at a given time t, while the explanatory variables are the traffic count in each condition (congested and uncongested)

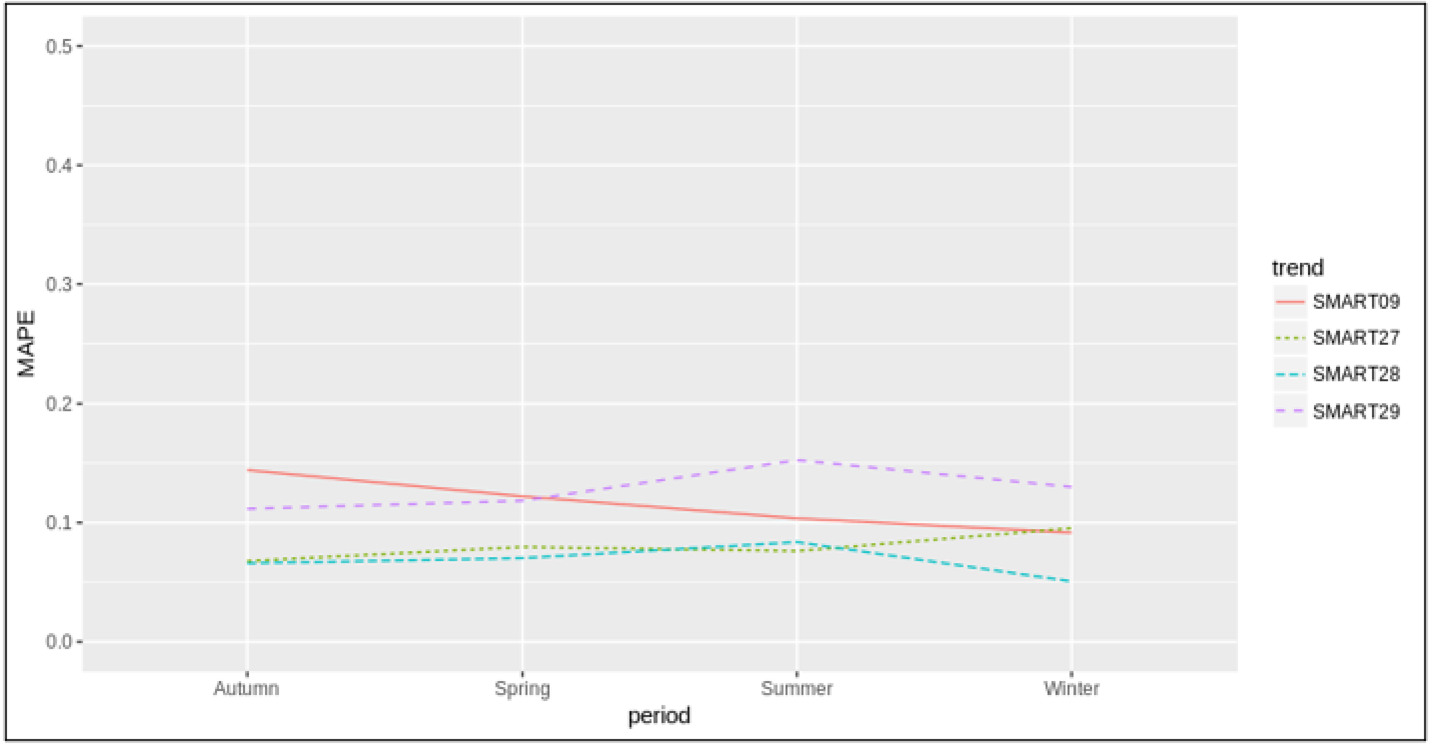
Model

- We estimated the K_1, K_2 for a number of sensors and in all of them the multilinear regression resulted to be significant producing the values for the coefficients with *p-value* in the range of p-val=2e-16, and *t-value* > 19 in all cases, for all coefficients.

- The *R-squared* of the models are also statistically significant, typically greater than 0.7 in most cases, which means that the models typically explain 70% of the variability of the response data around their mean in each hour of the day.

Results

- The model results in terms of MAPE at CO2 sensor locations in traffic periods when uncongested and congested traffic situations arise.



The mean absolute percentage error is close to 10% for each sensor location and season. Annually, the related uncertainty is 9.1% admitting a minimum of 5%.

Results

	Winter				Autumn			
Air Sensor	K_1	K_2	V_1	V_2	K_1	K_2	V_1	V_2
SMART09	230.0	681.3	37.4	3.9	317.7	791.5	36.5	3.9
SMART27	160.8	349.7	46.0	1.0	161.7	321.7	44.0	1.0
SMART28	219.6	386.7	36.0	1.0	253.1	352.3	35.0	1.0
SMART29	296.0	732.0	35.1	1.5	355.5	520.0	53.9	1.5
MEAN	226.6	537.4	38.6	1.8	272.0	496.3	42.3	1.8
	Summer				Spring			
Air Sensor	K_1	K_2	V_1	V_2	K_1	K_2	V_1	V_2
SMART09	184.0	709.4	39.8	3.9	217.8	619.2	35.2	3.9
SMART27	133.6	323.3	53.2	1.0	150.4	317.5	51.5	1.0
SMART28	290.3	383.2	36	1.0	274.0	381.5	34.0	1.0
SMART29	264.5	643.7	46.9	1.5	315.3	589.6	57.0	1.5
MEAN	218.1	514.9	43.9	1.8	239.3	476.9	44.4	1.8

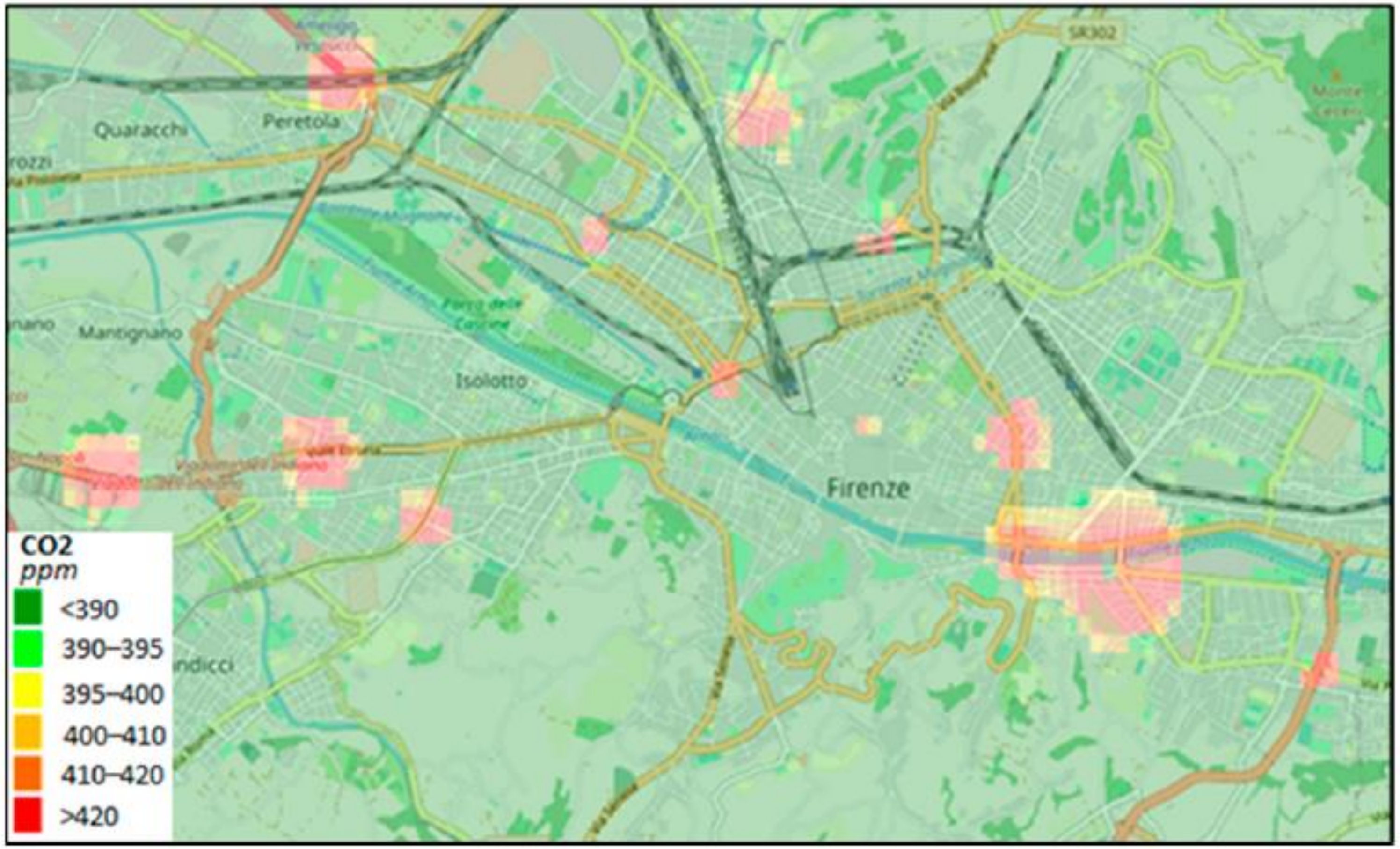
Results

- The estimated (mean) values of K_2 and K_1 can be also used to compute the CO2 amount at the traffic sensors' locations which are far from air quality sensors.

- This allows to estimate the amount of CO2 emissions in locations where air quality sensors are not placed.

- Since Florence Municipality admits many traffic sensors in scattered positions, then the CO2 data can be also estimated in the whole area by applying interpolation methods.

Results



An example of **CO2 heatmap** in Florence Municipality (at 8 AM in a working spring day).

TFR in Trafair Project

FROM DATA TO DIGITAL TWIN

FOR SMART MOBILITY

TRAFAIR

Understanding traffic flows to improve air quality

Co-financed by the Connecting Europe Facility of the European Union

TRAFFIC SENSORS

→ TRAFFIC MODEL → AIR POLLUTION DISPERSION MODEL

TRAFFIC FLOW

AIR QUALITY FORECAST

Air quality forecasts

Input data for air quality dispersion algorithm:

- Traffic vehicle analysis: sensors data, street graph and reconstruction model.
- Emission factors for vehicles (NO, NO2, NOX, CO).
- Vehicle fleet composition.
- 3D shape of the buildings.
- Weather forecast (wind fields and solar radiation).

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Vehicle fleet composition

- Information about the type of vehicles running in the streets in a given domain.

- Usually, it is assumed that these vehicles are those registered at the local transportation office, which can then be a source for this data. Another source, for Italy, is the Italian Automobile Club.

- This data describes the number of vehicles detailed for: emission standards (e.g. Euro I, Euro II, Euro III etc…), class (e.g. motorbike, passenger car, light duty vehicle, etc…), fuel (e.g. gasoline, diesel, compressed natural gas, etc…) and engine size (1 litre, 1.2 litres etc…).

3D shape of the buildings

- 3D shape of the buildings: for the simulation domain, including all or most of the urban area, it is needed a vector file (either an ESRI shapefile, or similar GIS vector format).

- This file needs to describe the horizontal boundaries of each building and its associated height.

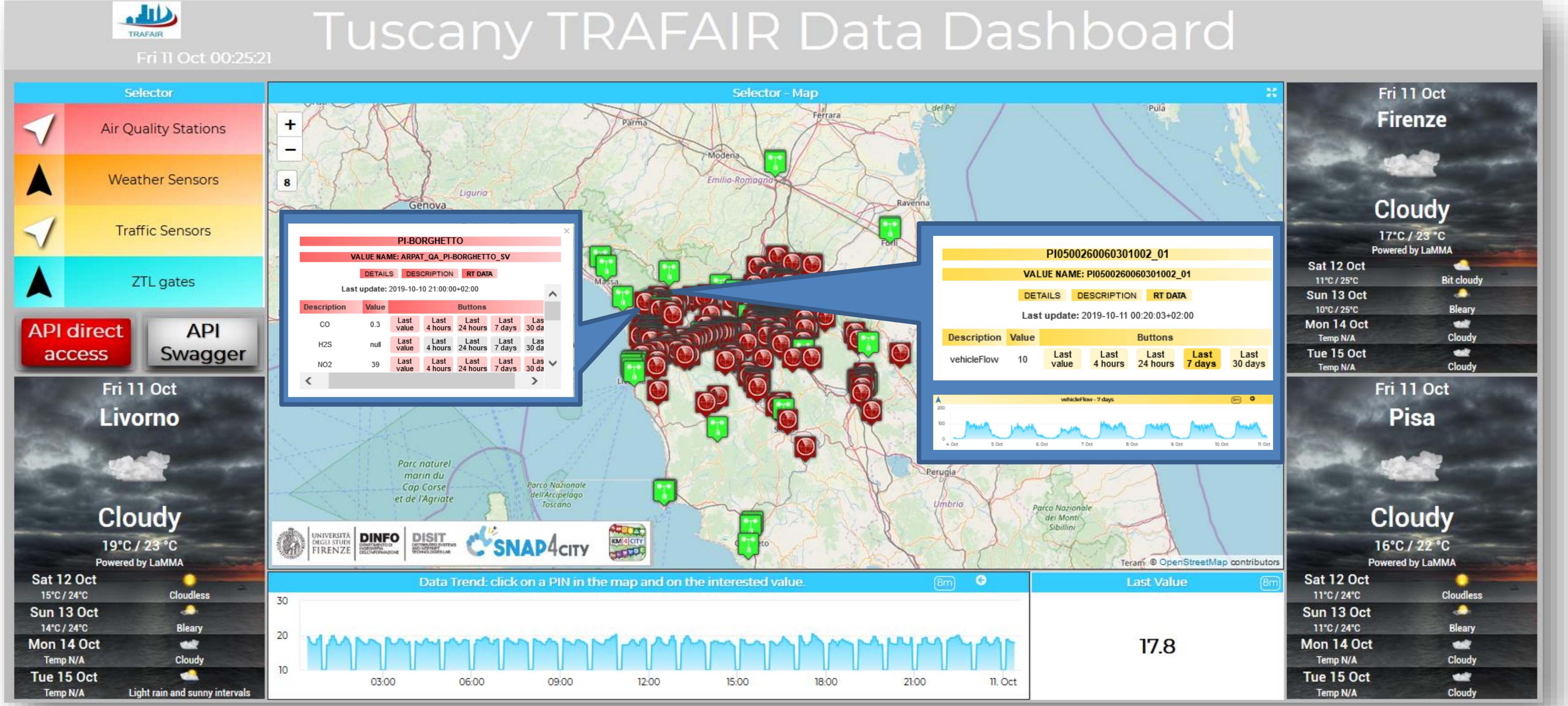
Weather data (forecast)

- Atmospheric pollutants dispersion is driven by local meteorology, for this reason a 24-48 hours weather forecast over an area covering the urban city center is needed.

- 3-D reconstruction of the wind field requires data of wind speed and wind direction at hourly time step from at least one point within the simulation domain (or as close as possible), in the form of vertical profile. Secondly, in order to estimate the pollutants mixing into the atmosphere, it is important to categorize the amount of atmospheric turbulence present at any given time.

TRAFAIR Data Dashboard:
Livorno, Firenze, Pisa

https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTUxNQ==



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Air quality forecast: GRAL model

- GRAL model: Lagrangian dispersion model developed at the Graz University of Technology, Institute for Internal Combustion Engines and Thermodynamics. http://lampz.tugraz.at/~gral/
- The complete source code is published under the GNU/GPL 3 licence: https://github.com/GralDispersionModel

Features:

- Tracking of particles moving on trajectories within a 3-D windfield.
- Computational Fluid Dynamics model for the flow calculation around buildings.
- Dispersion of chemically non-reactive pollutants.

GRAL model in Tuscany cities

Model settings:

- Model execution: every day.
- Model Prediction: next 48 hours.
- Temporal resolution: 1 hour.
- Horizontal spatial resolution: 4 x 4 m.
- 2 vertical levels: 3 and 6 m.
- Pollutant simulated: NOx.

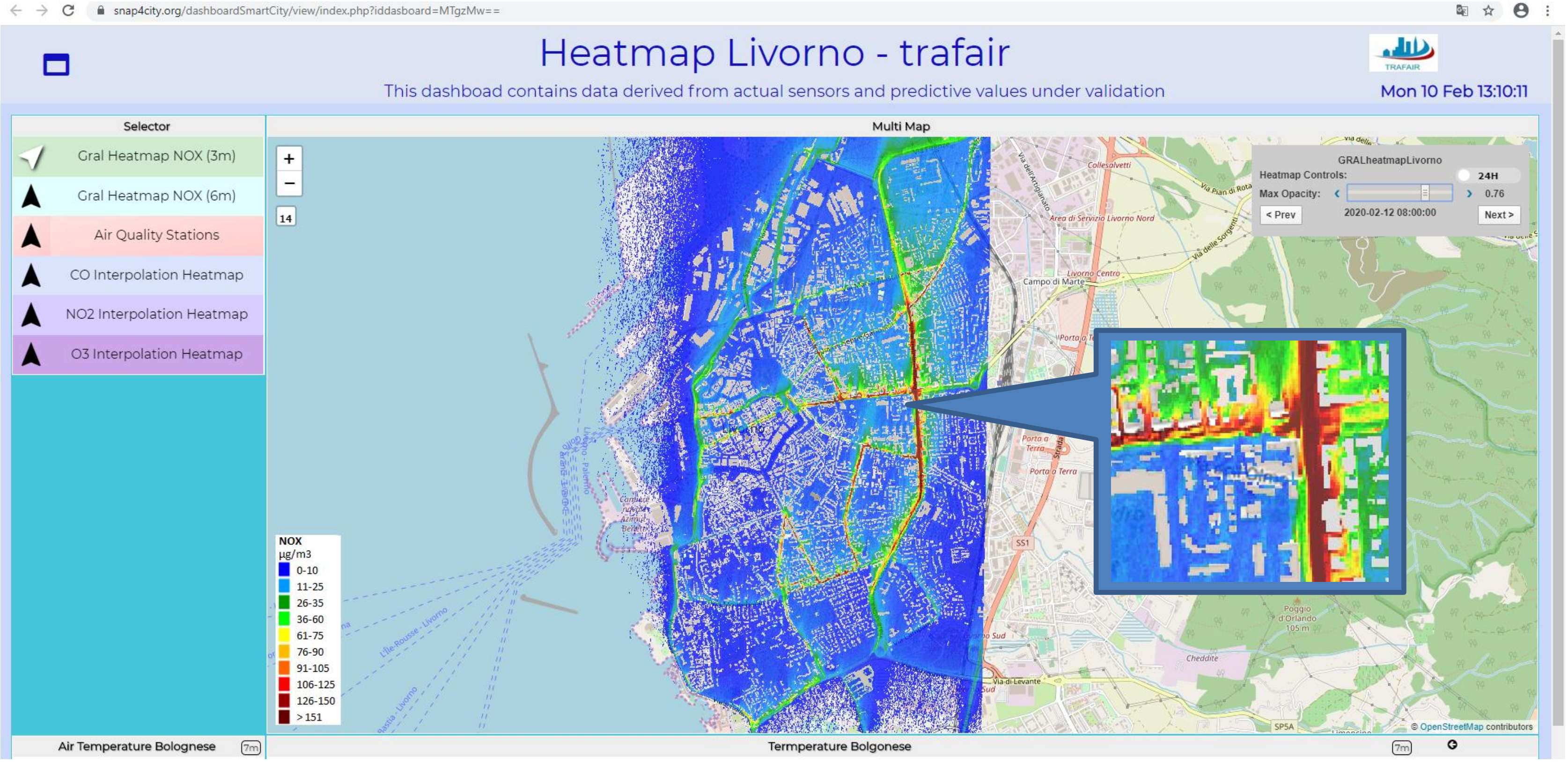
Speed up calculation Model:

- Parallelization approach: flow fields library generation.

GRAL model in Tuscany cities

Displaying results: Heatmaps

https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTgzMw==



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GRAL model in Tuscany cities

Displaying results: Heatmaps

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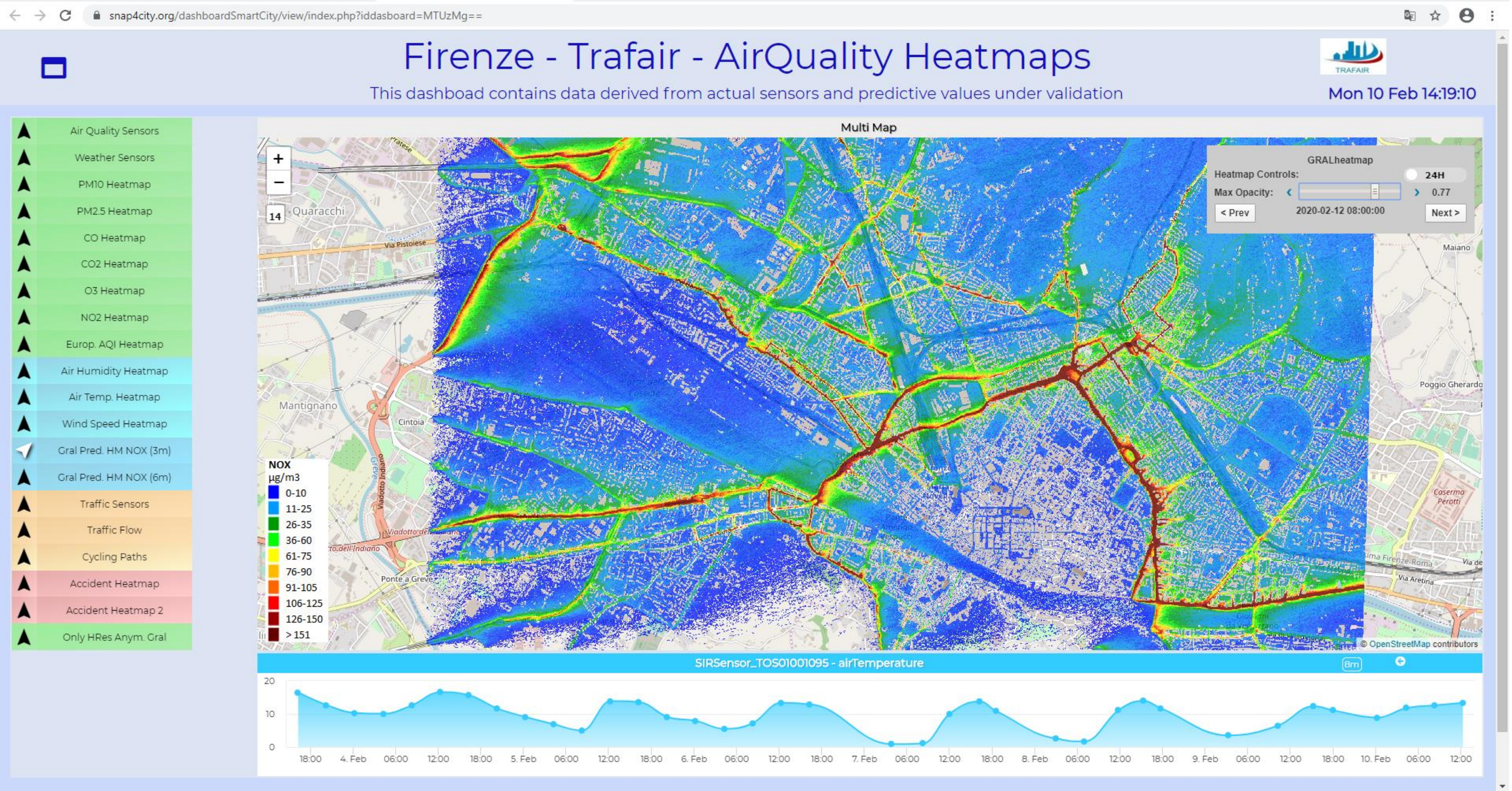

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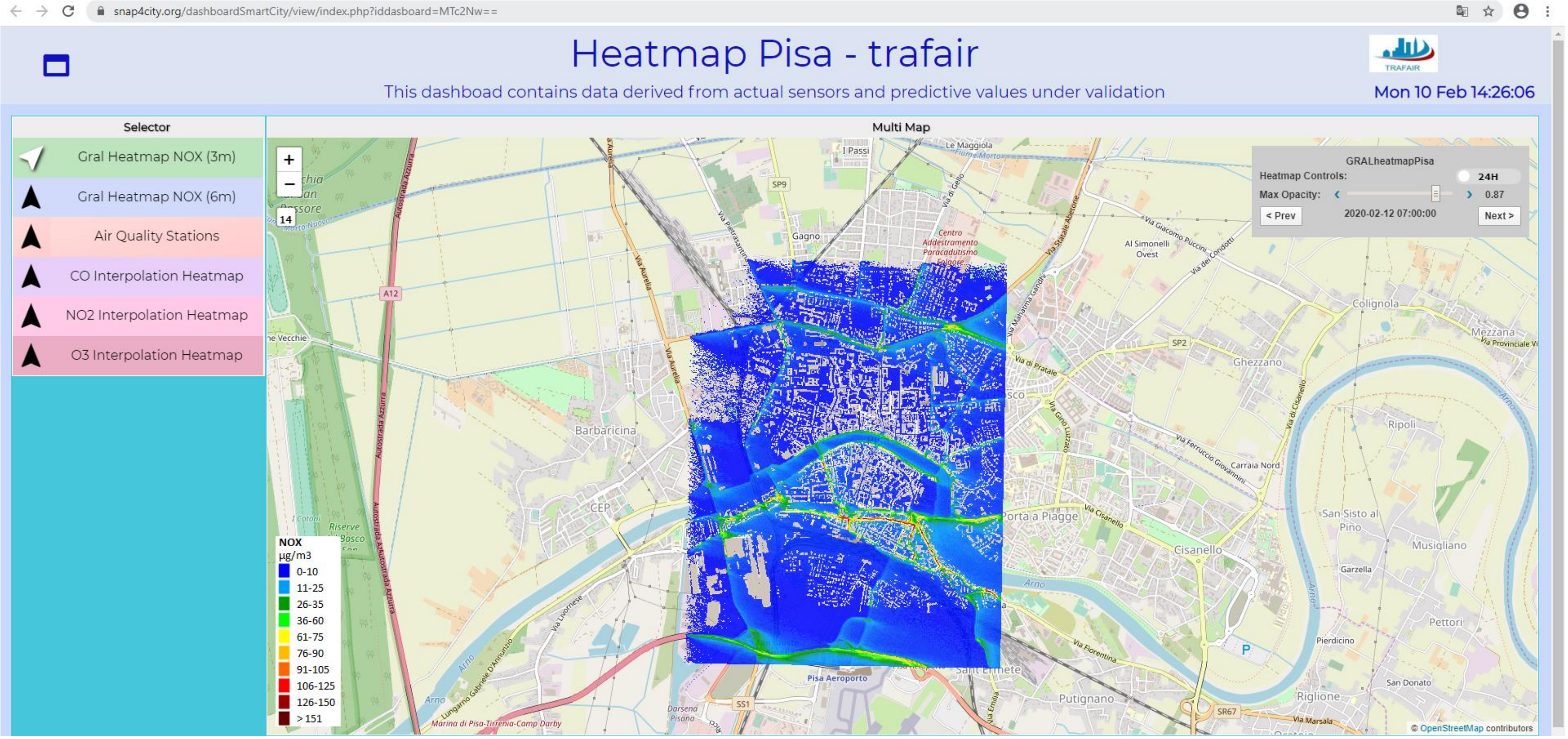
GRAL model in Tuscany cities

Displaying results: Heatmaps

https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc2Nw==



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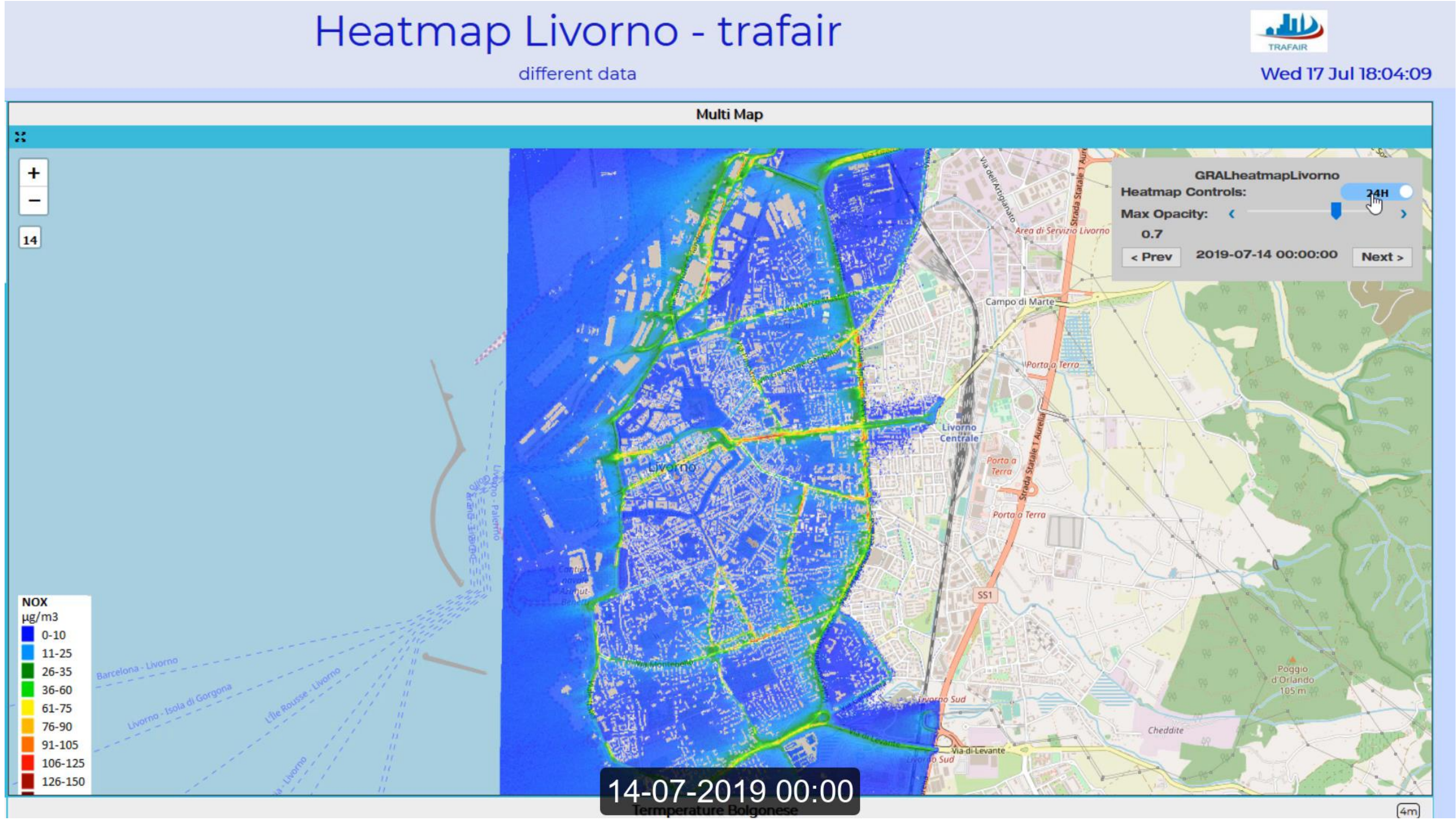
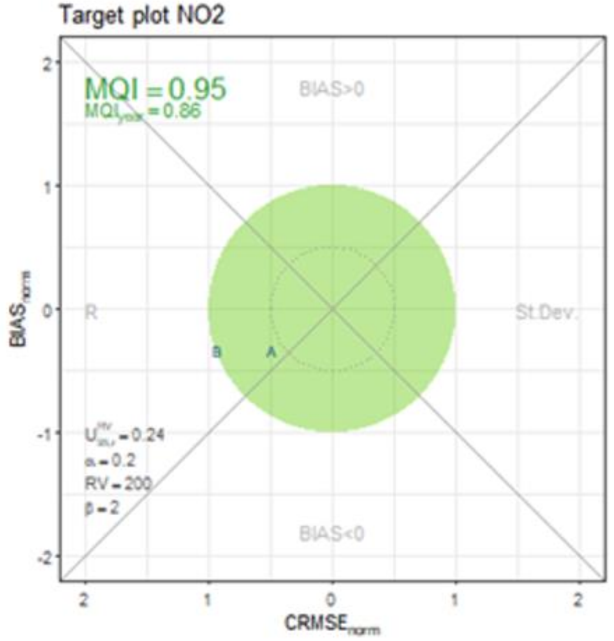
GRAL model in Tuscany cities

Displaying results: Heatmap Animation



Validation

- The environmental assessment of model has been performed by reproducing observed NOx concentrations at the AQM stations.
- Model error is compared with the standard MQO (Model Quality Objective) from observations.



Different scenarios in TFR

FROM DATA TO DIGITAL TWIN

FOR SMART MOBILITY

Motivations

- Smart city solutions have to cope with high complex situations of city scenarios addressing unexpected and planned events.
- On this topic, the major focus is often dedicated on vehicular traffic flow (and air pollution detection) which has a strong impact in the framework of urban behaviors.
- Closing a part of a city is an extreme solution, while less critical situations such as changing road direction, closing a single road, may be more frequent and less complex to be managed.

Motivations

- When such closures/changes are planned, there is time to identify the best solutions to maintain high quality of services.

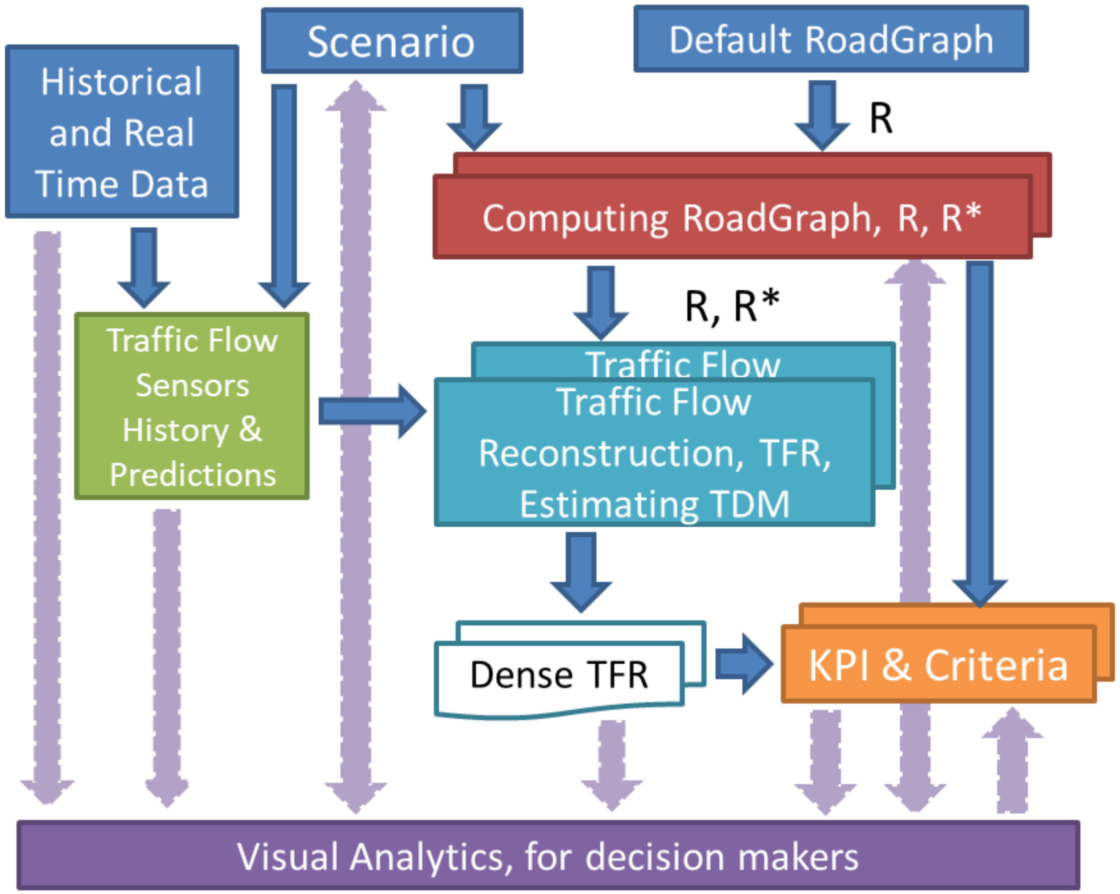
- In case of unplanned events, we have short time to understand (first of all) how the traffic would react as to the changes in place.

Goal

- Understand how the vehicular traffic would react with respect to a hypothetical scenario in order to mitigate such outcomes.

- A formalized approach is needed in order to identify the scenario constraints.

General idea: schema in TFR



Formalization

- Each scenario is denoted as SC_{ID} , and it is identified by a unique ID, a description, involved areas, a set of time intervals and additional constraints, such as any category of users or vehicles which have to be restricted/enabled.

A Scenario is formalized as tuple:

$$SC_{ID} = \{ID, D, \boldsymbol{A}, \boldsymbol{T}, \boldsymbol{C}, R\}$$

Formalization

where:

- ID is the unique Identifier of the scenario;
- D is a textual description of the scenario;
- $\boldsymbol{A}$ is a simple or multiply-connected blocked Area, that is a set composed by one or multiple blocked areas: $\boldsymbol{A} = \{A_1, A_2, \dots, A_N\}$, where N is the number of blocked Areas;
- $\boldsymbol{T}$ represents a set of time slots or intervals;
- $\boldsymbol{C}$ is a set of blocking constraints representing which transportation mean has been blocked/limited
- R is the reference road graph network.

Formalization

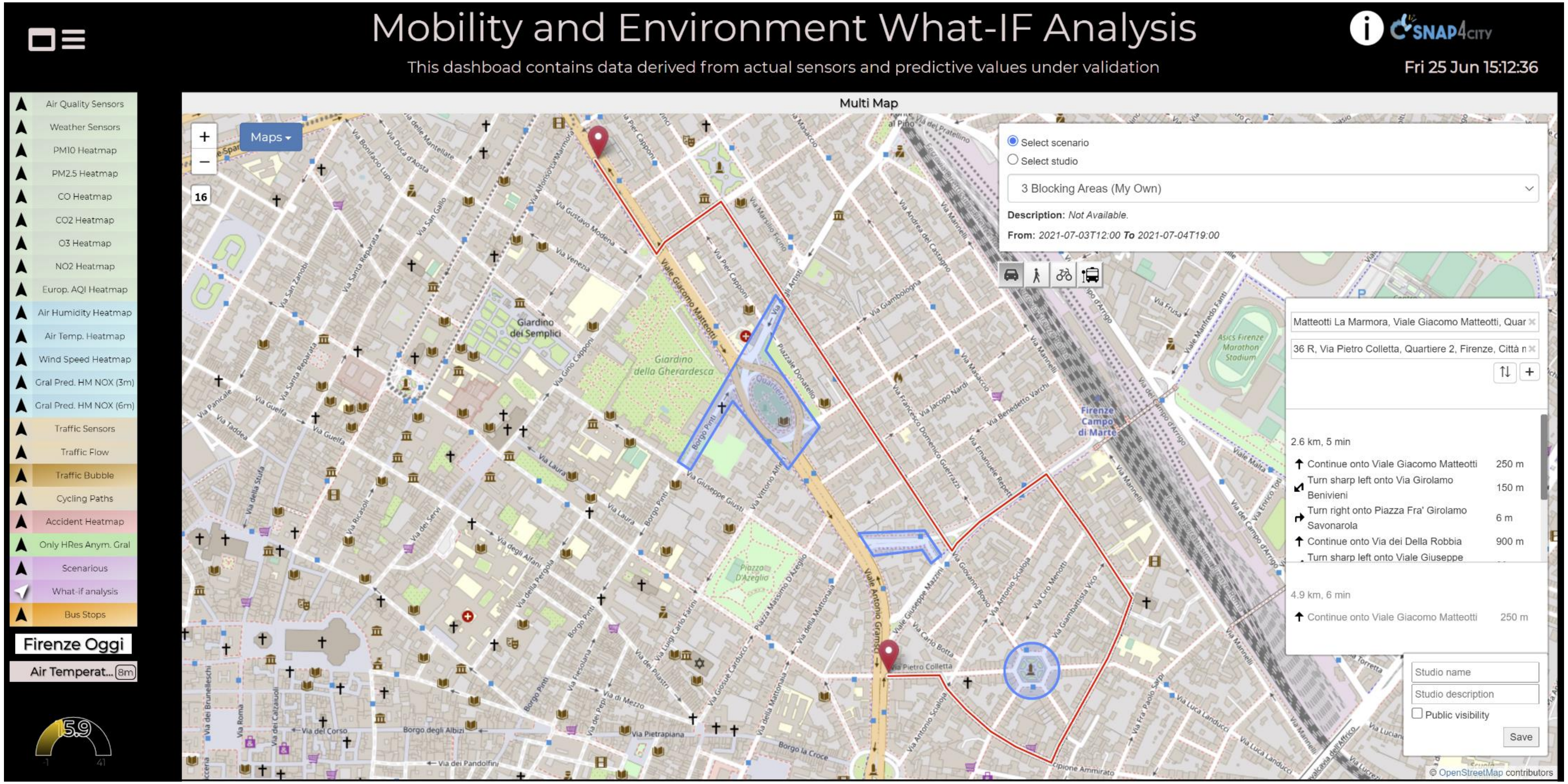
The impact of the application of a certain scenario $SC_{i,\widehat{\boldsymbol{T}}} = \{i, D_i, \boldsymbol{A}_i, \widehat{\boldsymbol{T}}, \boldsymbol{C}_i, R^*\}$, where R^* is the modified Road Graph starting from R, should be compared with:

- Others scenario $SC_{j,\widehat{\boldsymbol{T}}} = \{j, D_j, \boldsymbol{A}_j, \widehat{\boldsymbol{T}}, \boldsymbol{C}_j, R^*\}$,

- original scenario (without any restrictions), which is called the UnChanged Scenario, $SC\_UC_{i,\widehat{\boldsymbol{T}}} = \{i, D_i, \emptyset, \widehat{\boldsymbol{T}}, \emptyset, R\}$.

at the same time slots $\widehat{\boldsymbol{T}}$.

Tool



Mobility and Environment What-IF Analysis
This dashboad contains data derived from actual sensors and predictive values under validation
Fri 25 Jun 15:12:36
Air Quality Sensors
Weather Sensors
PM10 Heatmap
PM2.5 Heatmap
CO Heatmap
CO2 Heatmap
O3 Heatmap
NO2 Heatmap
Europ. AQI Heatmap
Air Humidity Heatmap
Air Temp. Heatmap
Wind Speed Heatmap
Gral Pred. HM NOX (3m)
Gral Pred. HM NOX (6m)
Traffic Sensors
Traffic Flow
Traffic Bubble
Cycling Paths
Accident Heatmap
Only HRes Anym. Gral
Scenarious
What-if analysis
Bus Stops
Firenze Oggi
Air Temperat...
Multi Map
Maps
Select scenario
Select studio
3 Blocking Areas (My Own)
Description: Not Available.
From: 2021-07-03T12:00 To 2021-07-04T19:00
Matteotti La Marmora, Viale Giacomo Matteotti, Quar
36 R, Via Pietro Colletta, Quartiere 2, Firenze, Città m
2.6 km, 5 min
Continue onto Viale Giacomo Matteotti 250 m
Turn sharp left onto Via Girolamo Benivieni 150 m
Turn right onto Piazza Fra' Girolamo Savonarola 6 m
Continue onto Via dei Della Robbia 900 m
4.9 km, 6 min
Continue onto Viale Giacomo Matteotti 250 m
Studio name
Studio description
Public visibility
Save
© OpenStreetMap contributors

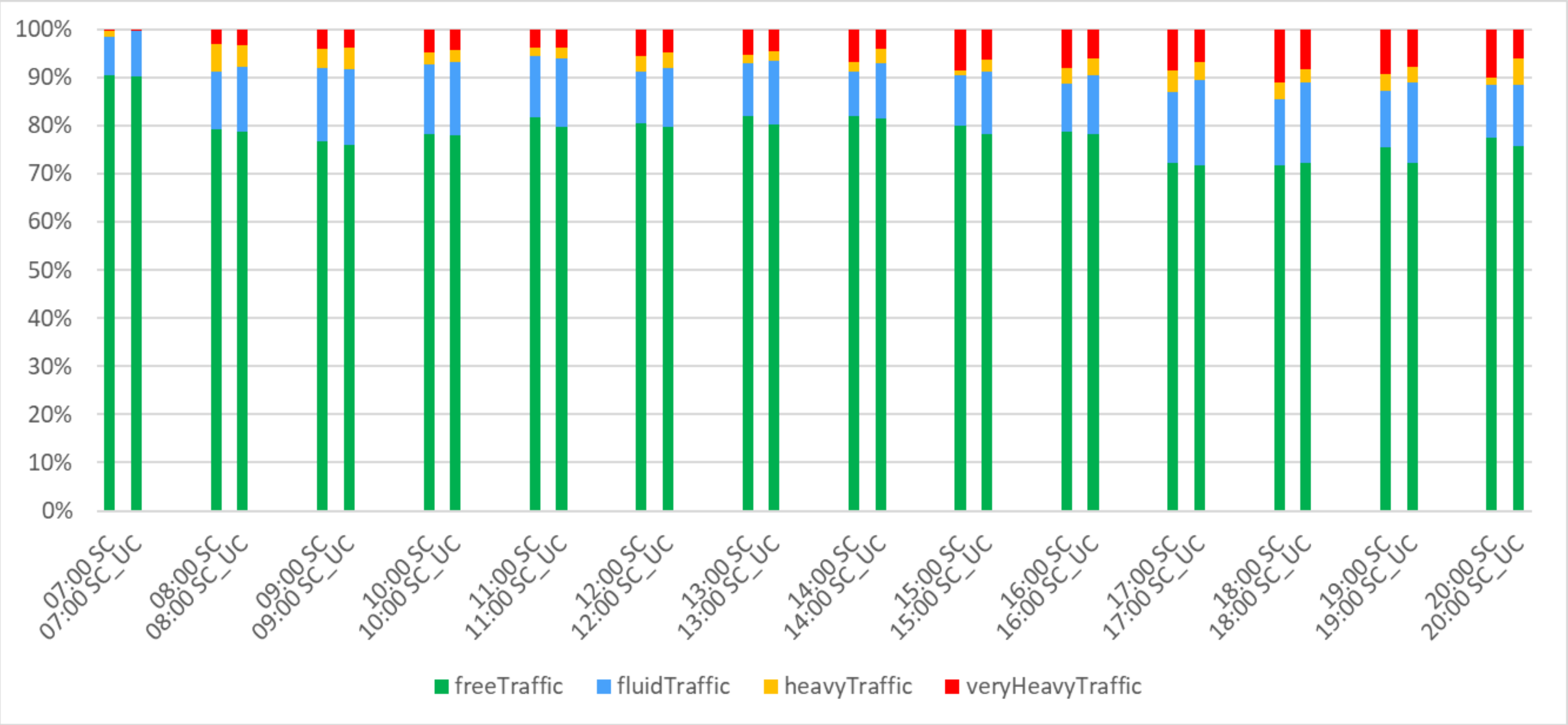
Key Performance Indicators (KPI)

- KPIs are considered to assess globally city traffic conditions, therefore the impact of changes has to be calculated on the basis of the computed dense TFR, taking into account the different Road Graphs of each scenario, $SC_{i,\hat{\boldsymbol{T}}}$.

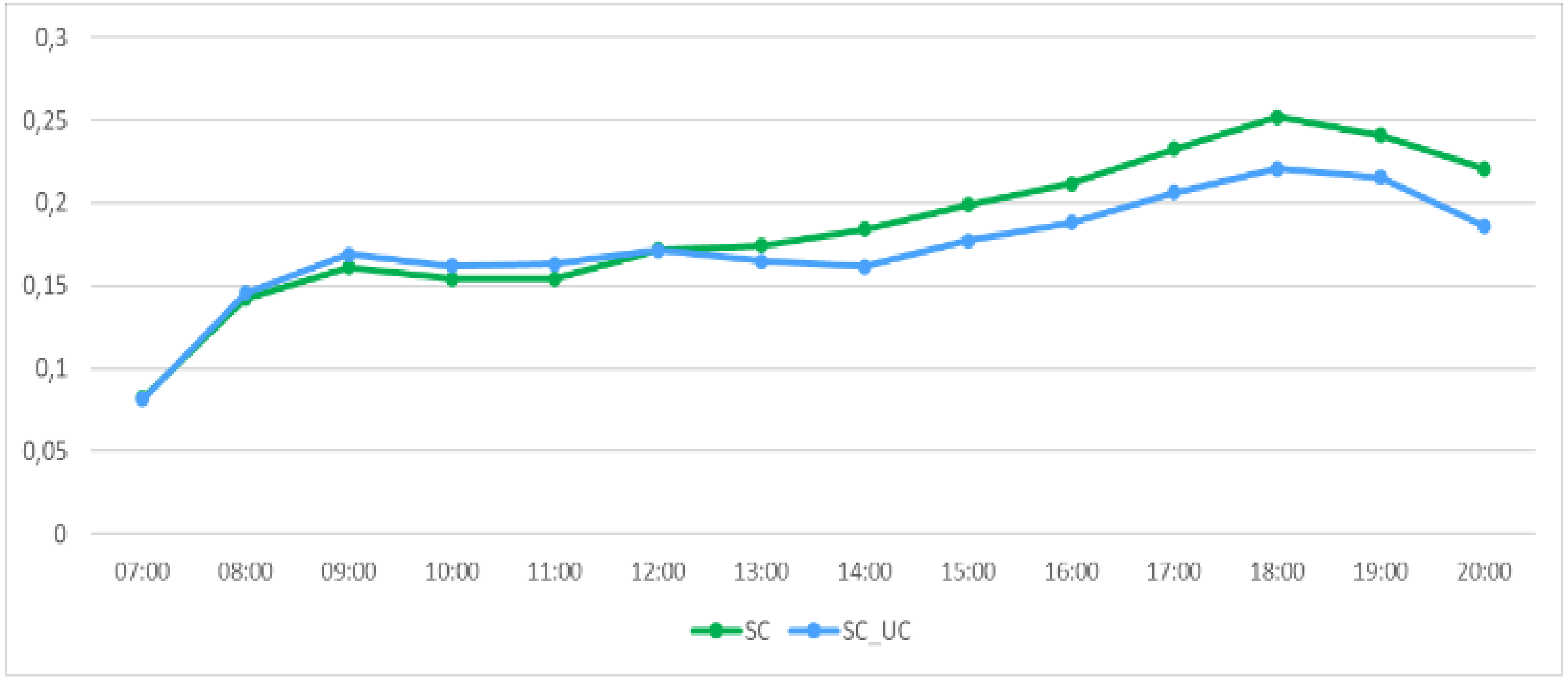
- Each estimation of KPI has to be compared against values for the same time slots $\hat{\boldsymbol{T}}$, and it is obtained in different conditions against the original scenario (that is, without changes on Road Graph) called UnChanged Scenario, $SC\_UC_{i,\hat{\boldsymbol{T}}}$.

$$KPI(SC_{i,\hat{T}}) = KPI_1(SC_{i,\hat{T}}) \cup \ldots \cup KPI_n(SC_{i,\hat{T}}).$$

Traffic KPI

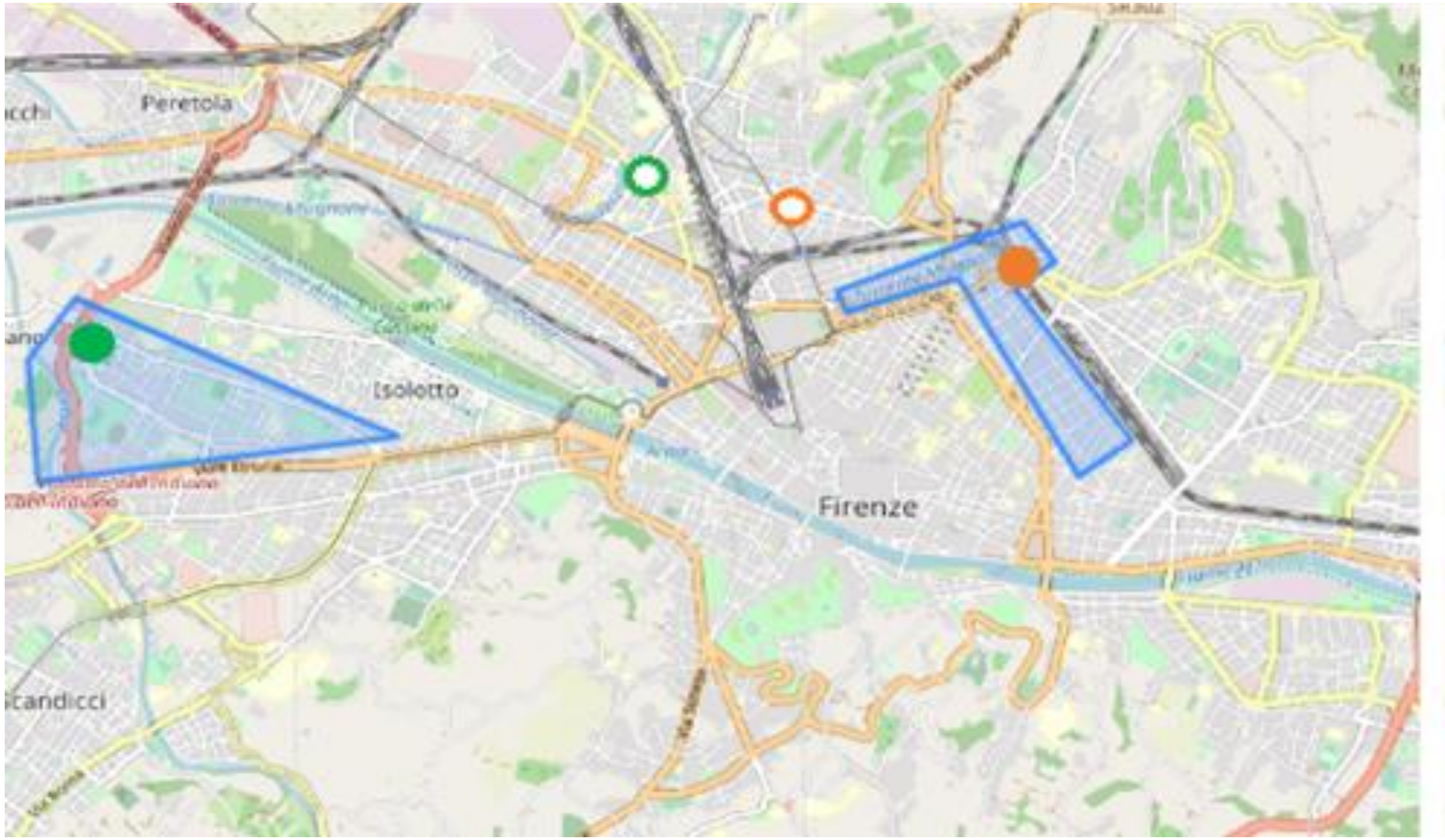

100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
07:00 SC
07:00 SC_UC
08:00 SC
08:00 SC_UC
09:00 SC
09:00 SC_UC
10:00 SC
10:00 SC_UC
11:00 SC
11:00 SC_UC
12:00 SC
12:00 SC_UC
13:00 SC
13:00 SC_UC
14:00 SC
14:00 SC_UC
15:00 SC
15:00 SC_UC
16:00 SC
16:00 SC_UC
17:00 SC
17:00 SC_UC
18:00 SC
18:00 SC_UC
19:00 SC
19:00 SC_UC
20:00 SC
20:00 SC_UC
freeTraffic
fluidTraffic
heavyTraffic
veryHeavyTraffic

Saturation level KPI (also in air pollution context)



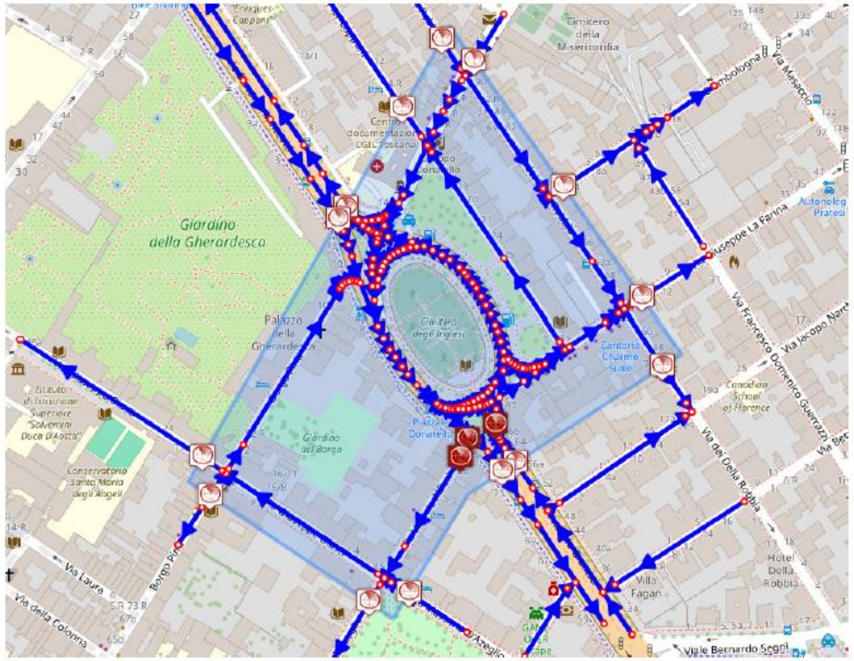
$$S(t) \cong \sum_{i=1}^{N} \frac{\rho_R(i,t)}{\rho_{max}(i)}$$

Topological KPI



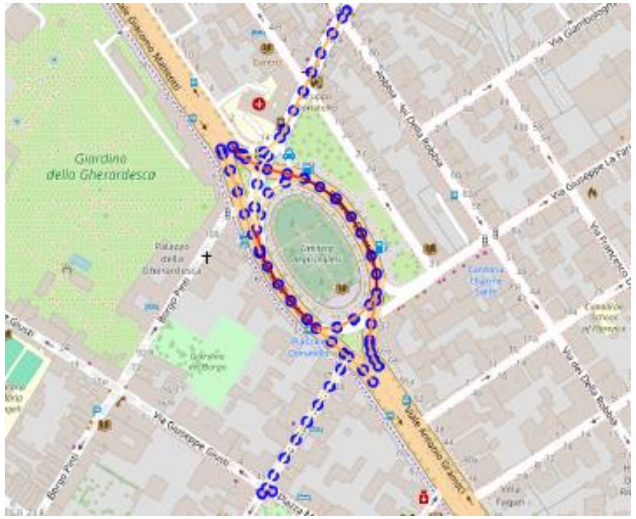
Micro – scale Scenario

- The case study where the reconstruction analytics, originally used for a macro-scale analysis, produces consistent results on the micro-scale.



Consistency test

The virtual sensors are considered to reproduce the same boundary conditions in the extracted graph

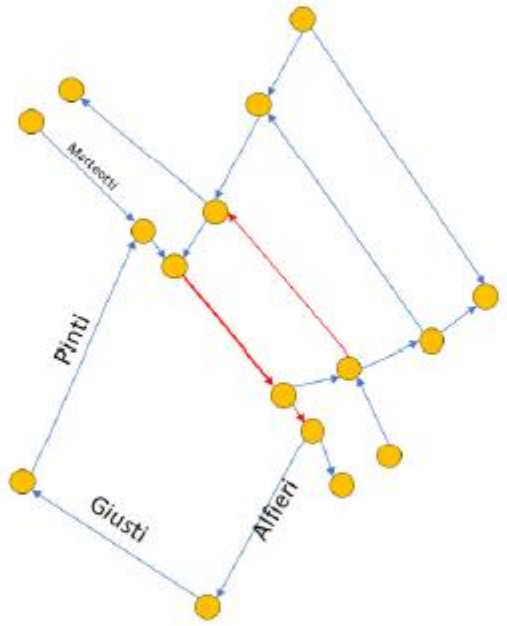


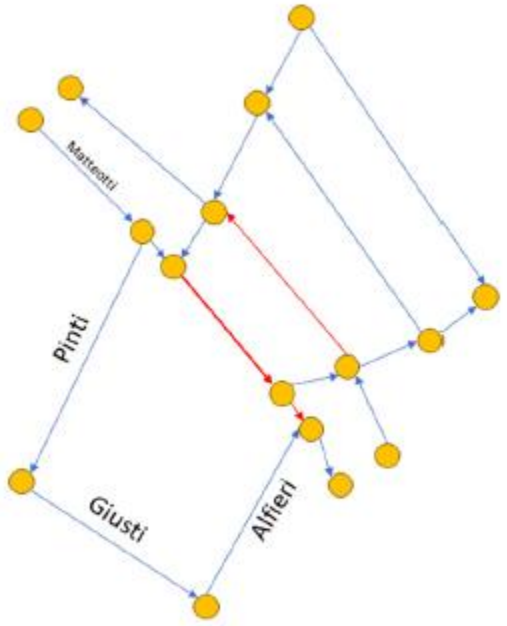
Consistency test

- The TFR algorithm produced almost identical reconstruction results on the defined micro-scale scenario with respect to the macro scale, showing an equal level of congestion on the corresponding road elements.

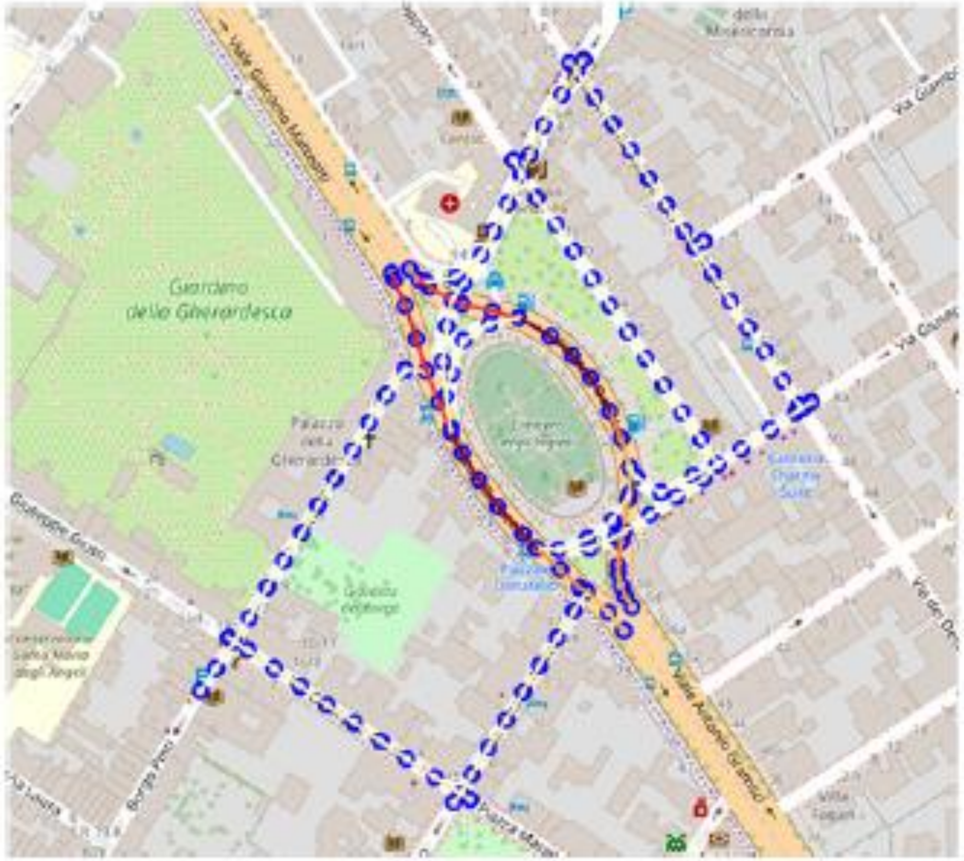
- Comparison of the traffic flow reconstruction (red line) from macro-scale and the TFR (blue line) on the scenario area of the 68 segments.

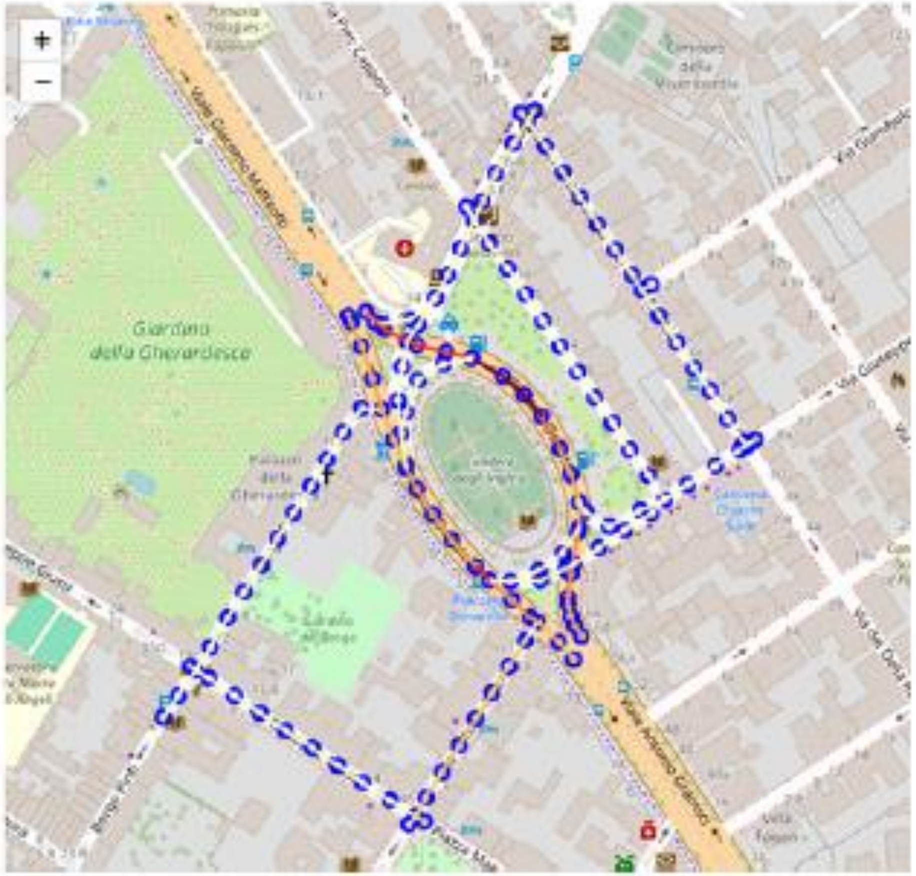
Scenario by changing direction



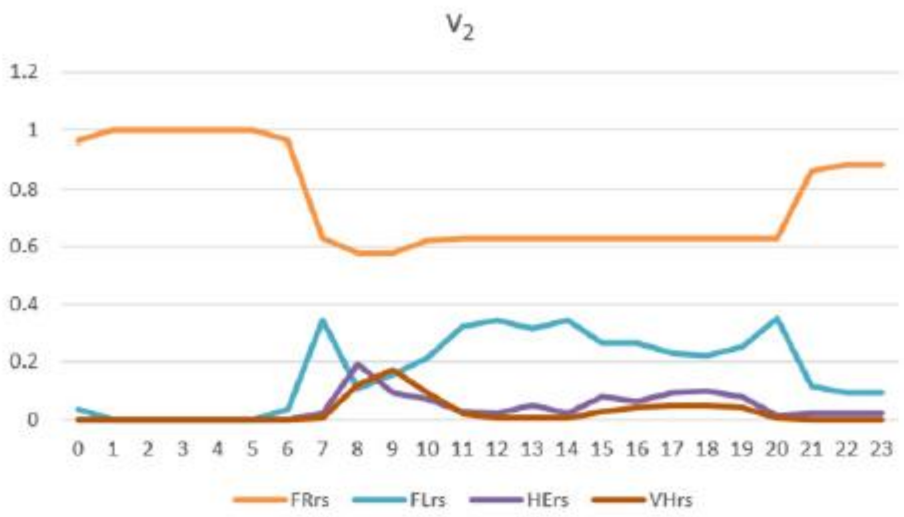


Scenario by changing direction





Scenario by changing direction: analytics



Importance of what-if analysis

- What-if analysis can help city councils and decision makers in planning and development activities by assessing the current urban status and performing simulations on multiple scenarios after changing specific elements of the urban context via KPI comparison.

Thanks for the attention