Optimization in transportation and logistics

M. Grazia Speranza

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Transportation science and logistics

1960 and ‘70

“Transportation science” emerged

“Transportation” meant traffic and public transportation

“Logistics” was a young field that referred to physical distribution and inventory management

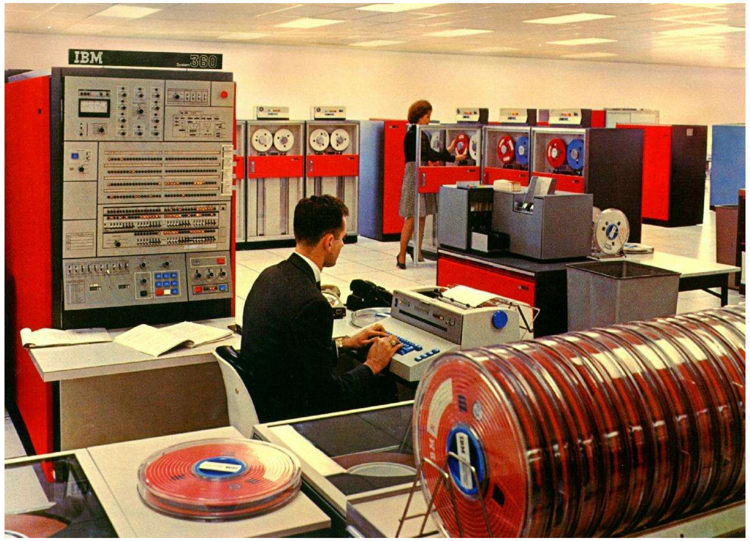
Programming languages:

1968 Logo

1970 Pascal

1972 C, Smalltalk, Prolog

1978 SQL



Transportation science and logistics

1990

“Transportation” included passenger and freight transportation

“Logistics” developed into “supply chain management”

Internet

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Transportation science and logistics

2000 and 2010

“Transportation and logistics” becomes systemic, collaborative and dynamic

Mobile apps

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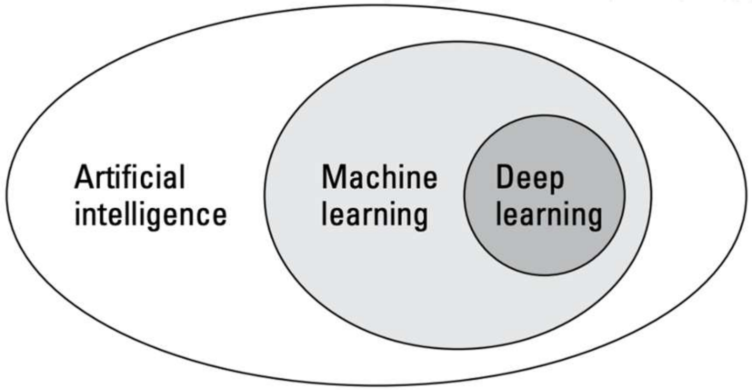
Transportation science and logistics

2020

“Transportation and logistics” focuses on data



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The contributions

Vehicle routing

Facility location

Warehouse management

Optimization:

trains and aircrafts

Traffic assignment

Network design

Crew management

Supply chain management

Bus scheduling

Inventory management

Production planning and scheduling

Directions

Collaborative

Systemic

Dynamic

Data-driven

Technology-driven

Fuel cost optimization:

An optimization opportunity enabled by the availability of data on the cost of fuel

Fuel cost optimization

Collaboration with a truck security company

Multiprotexion offers solutions that include:

- Security services
- GPS
- Real-time info about speed, fuel consumption, driving times, etc.

Fuel cost optimization

Route planning in long-haul transportation

Objectives: 1. cost of refueling and 2. route duration

Day-by-day availability of cost of fuel at each station

Archetti, Jabali, Mor, Simonetto, Speranza, Omega, 2022

Hours of service regulations

Regulations (EC) No 561/2006 and Directive 2002/15/EC

1. *Continuous driving rule*: 4.5 hours of driving, 45 minutes rest.
2. *Maximum daily driving rule*: 9 hours of driving, 11 hours rest.
3. *Maximum weekly driving rule*: 56 hours of driving, 45 hours rest.

Fuel cost optimization

- Milan metropolitan area:

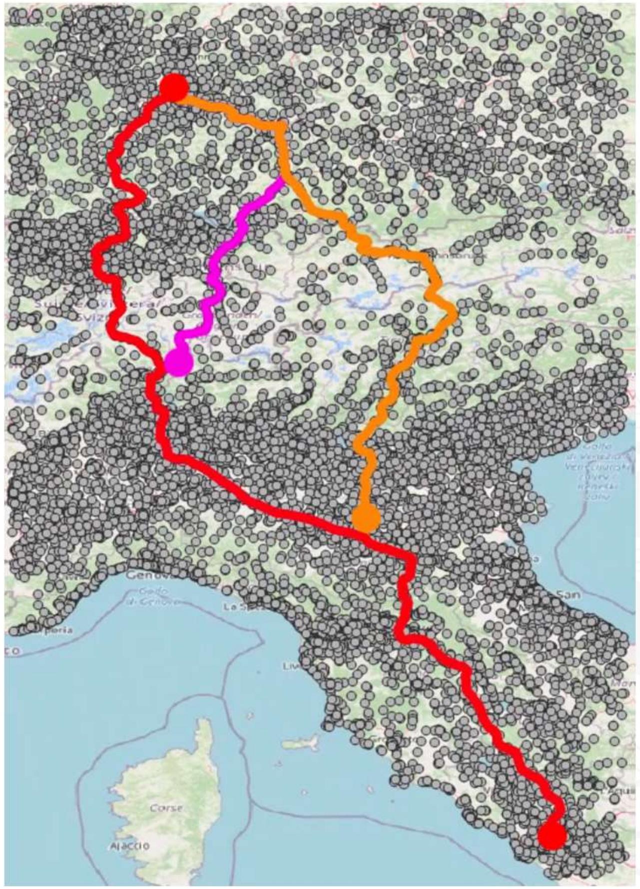
1575 km^2, 831 fuel stations.

- Path from Rome to Stuttgart:

1075 *km*, 1090 fuel stations within 5 *km*.

16249 fuel stations in the picture.

Data from: OpenStreetMaps + GraphHopper



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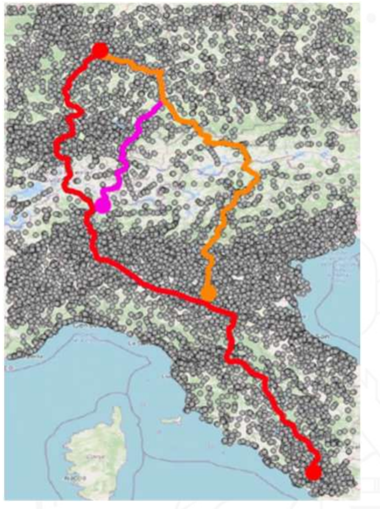
Fuel cost optimization



Types of stops:

- F: fuel
- B: 45 min rest
- D: daily rest
- W: weekly rest

7 combinations of stops: F, FB, FD, FW, B, D, W

Rome to Stuttgart: 113745 vertices, 13 billion edges

We cannot work on the complete graph

→ Dynamic building of the path, on the basis of vehicle and driver current status

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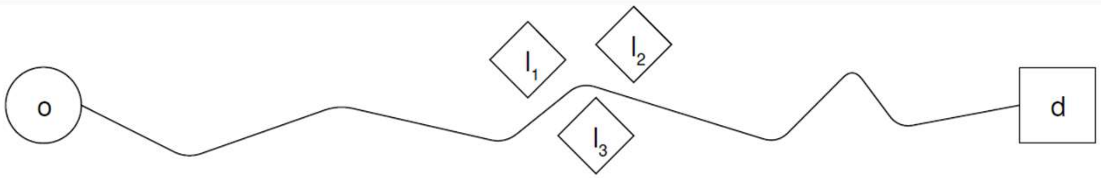
The ideas

1. Explore multiple paths

2. Consider refueling and resting locations only where *relevant*

- Between 10% and 5% of fuel left
- No further than 5% of maximum driving time remaining



3. Dynamically build multiple feasible paths

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Algorithm 1 Solution algorithm

Input: o, d, k
branchToDestination$(o,\ k)$
infeasibleArc := **selectInfeasibleArcToDestination**(tree)
while infeasibleArc != null **do**
  $S = \emptyset$
  $\bar{o}$:= origin of infeasibleArc
  Q := **findStopLocations**$(\bar{o}, d)$ (Section 4.1)
  for all $q \in Q$ **do**
    $S := S \cup$ **combineStopTypes**(q) (Section 4.2)
  end for
  for all $s \in S$ **do**
    create arc from the $\bar{o}$ to s
    branchToDestination(s, k)
  end for
  remove infeasibleArc $(\bar{o}, d)$
  infeasibleArc := **selectInfeasibleArcToDestination**(tree)
end while
Identify Pareto optimal paths
Output: Pareto optimal paths

Instances

Origin to destination

- 500 km: Freiburg im Breisgau (DE) to Maastricht (NL)
- 1000 km: Paris (FR) to Brescia (IT)
- 1500 km: Montreux (CH) to Timisoara (RO)

Status of driver

- b: just after a break, with half of the day and of the week hours remaining
- d: just after a daily rest, with half of the week hours remaining
- w: one working day remaining before a week rest

Status of vehicle

Initial fuel level: {10, 25, 50, 75, 100}% of a 500 liters tank

Fuel consumption: 3.5 km/liter

45 instances

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Assessment of results

Comparison with *current practice*, in absence of information and planning:

Stop where you need, when you need.

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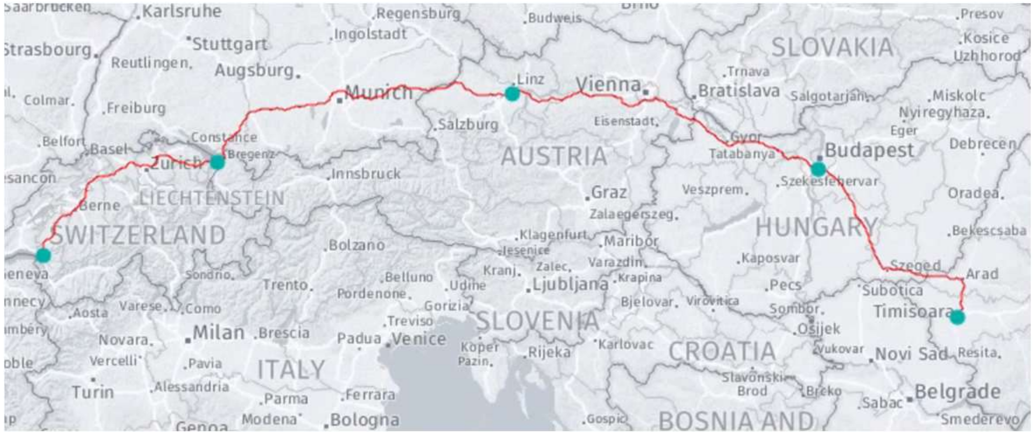
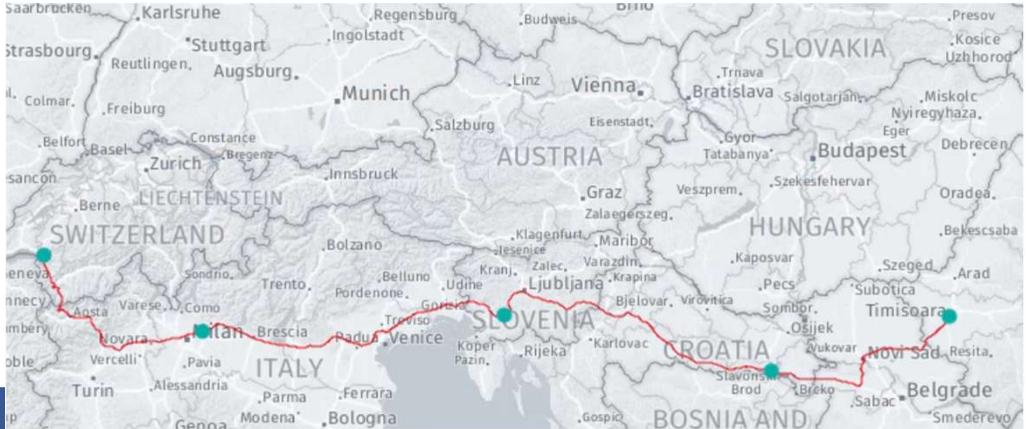
Results



468.49 Euro

61 hours 17 minutes



653.77 Euro

60 hours 58 minutes

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Results

- Up to 115 Euro of fuel saving (1500_b_10)
- Up to 1 hour 42 minutes time saving (1500_b_75)

- Up to 25% fuel saving (500_d_10)
- Up to 12% time saving (500_w_25)

Contribution:

An optimization model for a new real problem,

a heuristic and

computational results that prove the value of the approach against practice

Decision making in a bike-sharing system:

Tactical and operational decisions via simulation (with embedded optimization)

M.Grazia Speranza

Bike-sharing

Starting year: 2004

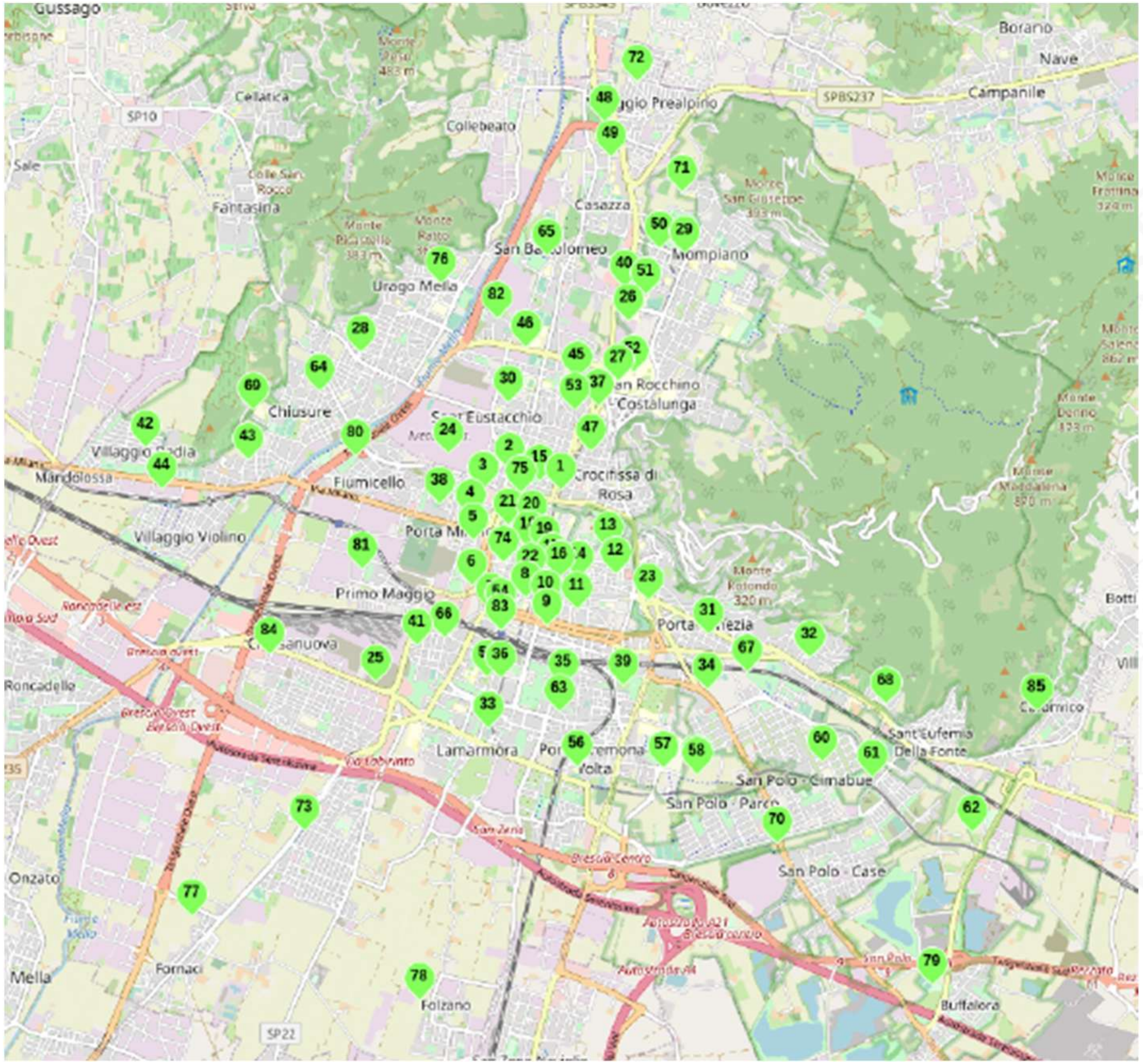
84 stations

460 bikes

19,634,889 km

Saving: 2,945,231 kg of CO_2

Free service



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Bike-sharing

Goal: To optimize the service quality to increase usage while keeping the cost of the service as low as possible

Bike-sharing

Questions from the CEO of Brescia Mobilità:

How can I understand if a decision we take (e.g., number of bikes, shifts of the drivers) is good or not?

Can we improve the real-time rebalancing service?

Bike-sharing

Layout

? Demand

Fleet and driver shifts

Strategic decisions: simulation

Real-time decisions: dynamic rebalancing

Angelelli, Mor, Speranza, C & IE, 2022

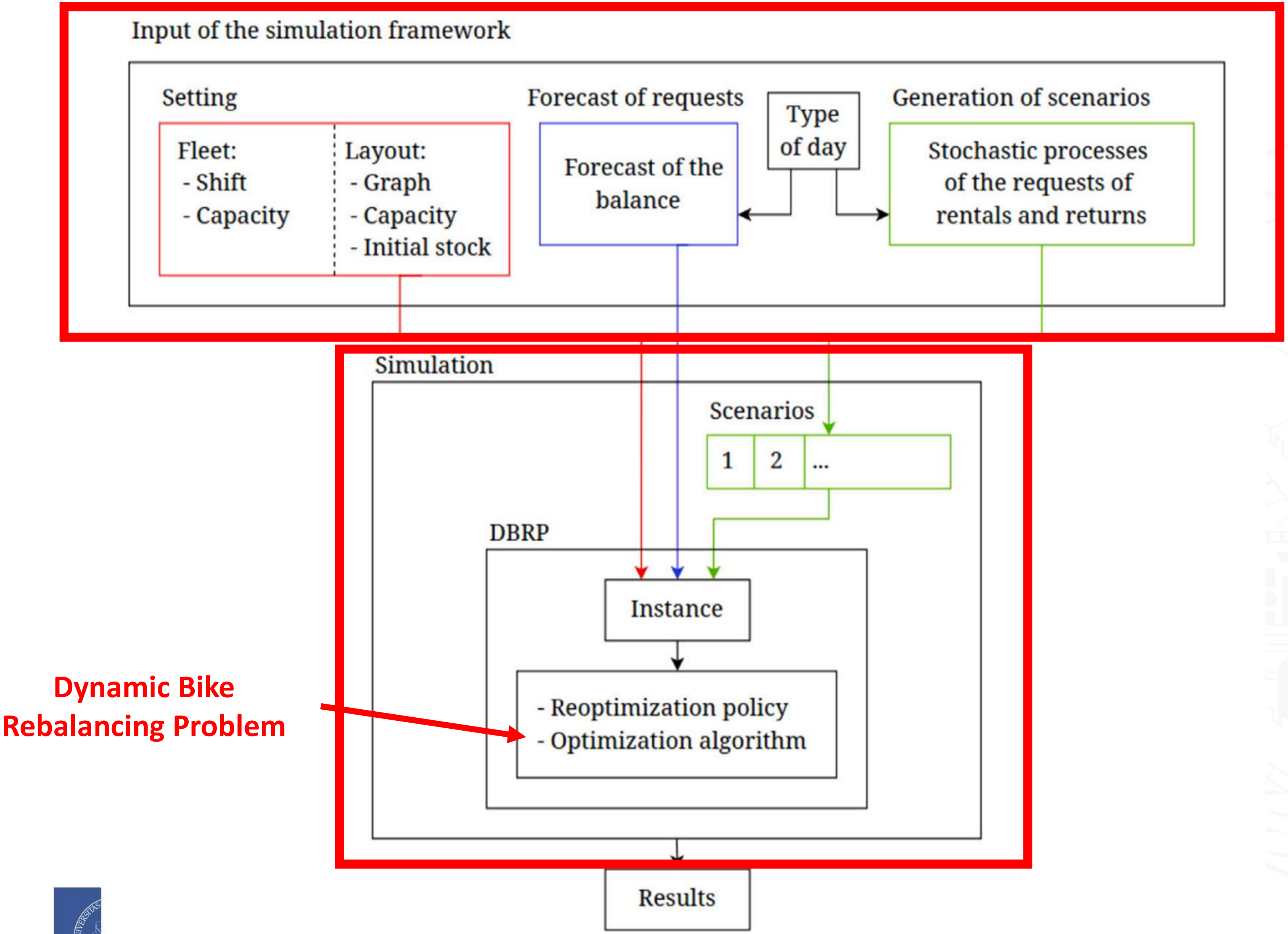
How can we forecast the demand?

Historical data:

- Month
- Working day/Saturday/Sunday
- Weather (sunny/rainy)

→

The company identified
12*3*2 typical days


Input of the simulation framework
Setting
Fleet:
- Shift
- Capacity
Layout:
- Graph
- Capacity
- Initial stock
Forecast of requests
Forecast of the balance
Type of day
Generation of scenarios
Stochastic processes of the requests of rentals and returns
Simulation
Scenarios
1
2
...
DBRP
Instance
- Reoptimization policy
- Optimization algorithm
Results
Dynamic Bike Rebalancing Problem

Dynamic rebalancing in bike-sharing

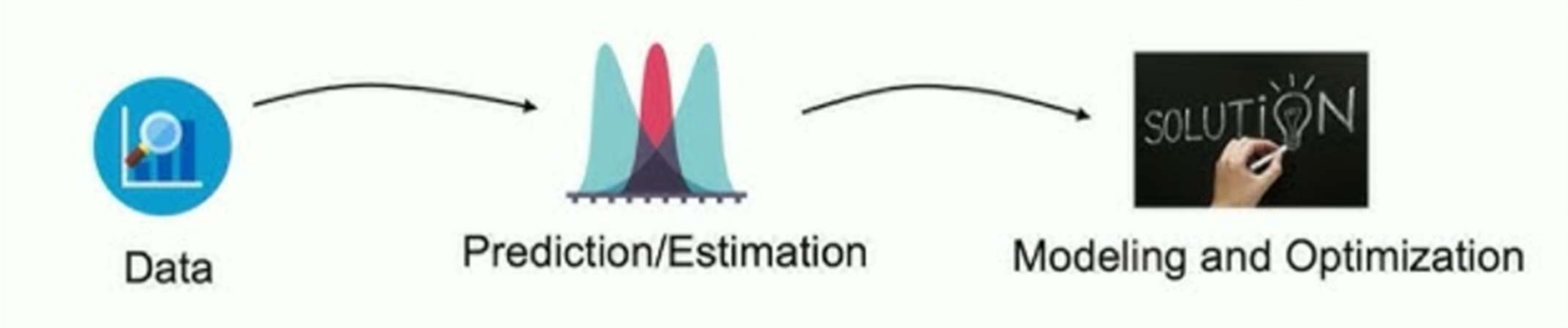
Drivers receive on an iPad instructions on:
- where to go
- how many bikes to download
- how many bikes to upload

Contribution:

A new simulation framework

and computational results on real data that show the benefits of the framework

Can we improve the results with better forecast?



Predict-then-optimize

Improving the forecast

Machine learning-based forecast of the demand

⬇

Improved results of the optimization

Angelelli, Mor, Orsenigo, Speranza, Vercellis, under revision, 2025

Location of recharging stations:

A location model for a real problem

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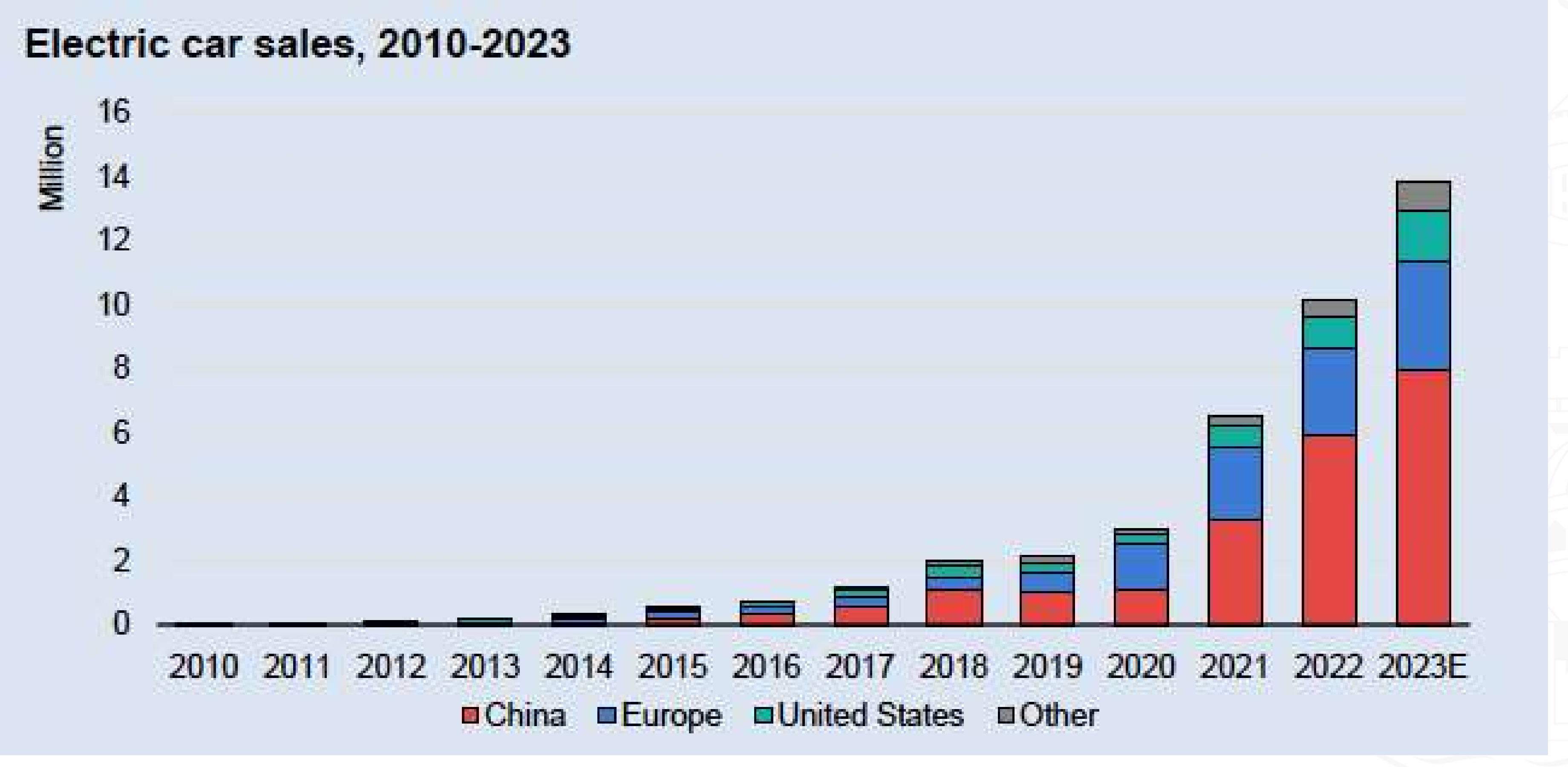
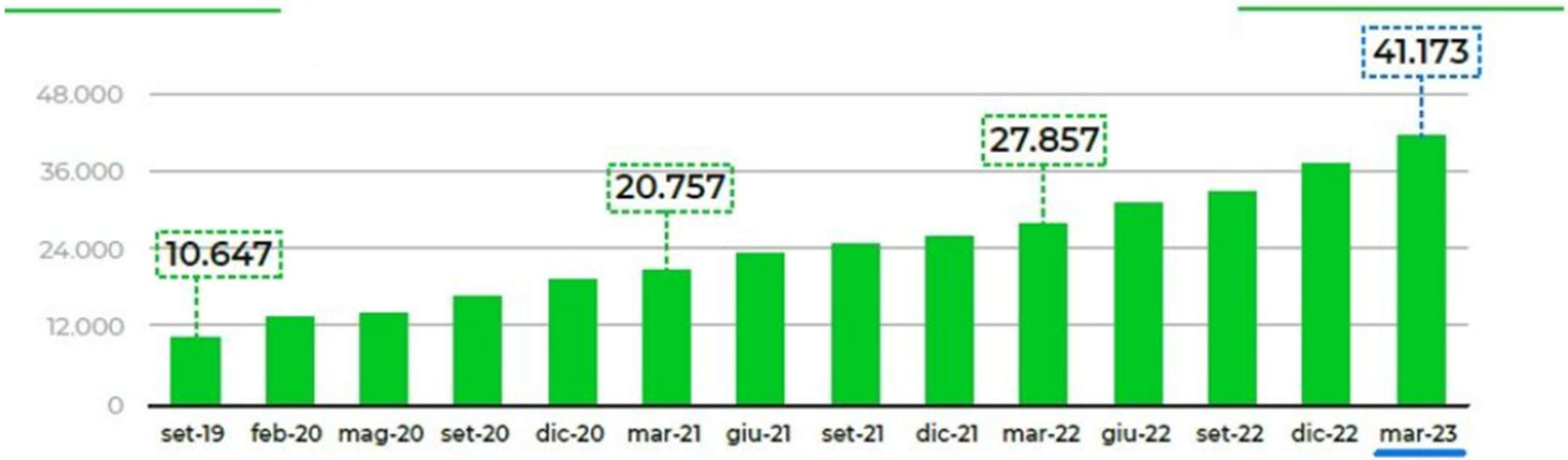
M.Grazia Speranza

Trend for electric vehicles



Trend for recharging points



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The location problem

Input: Potential locations

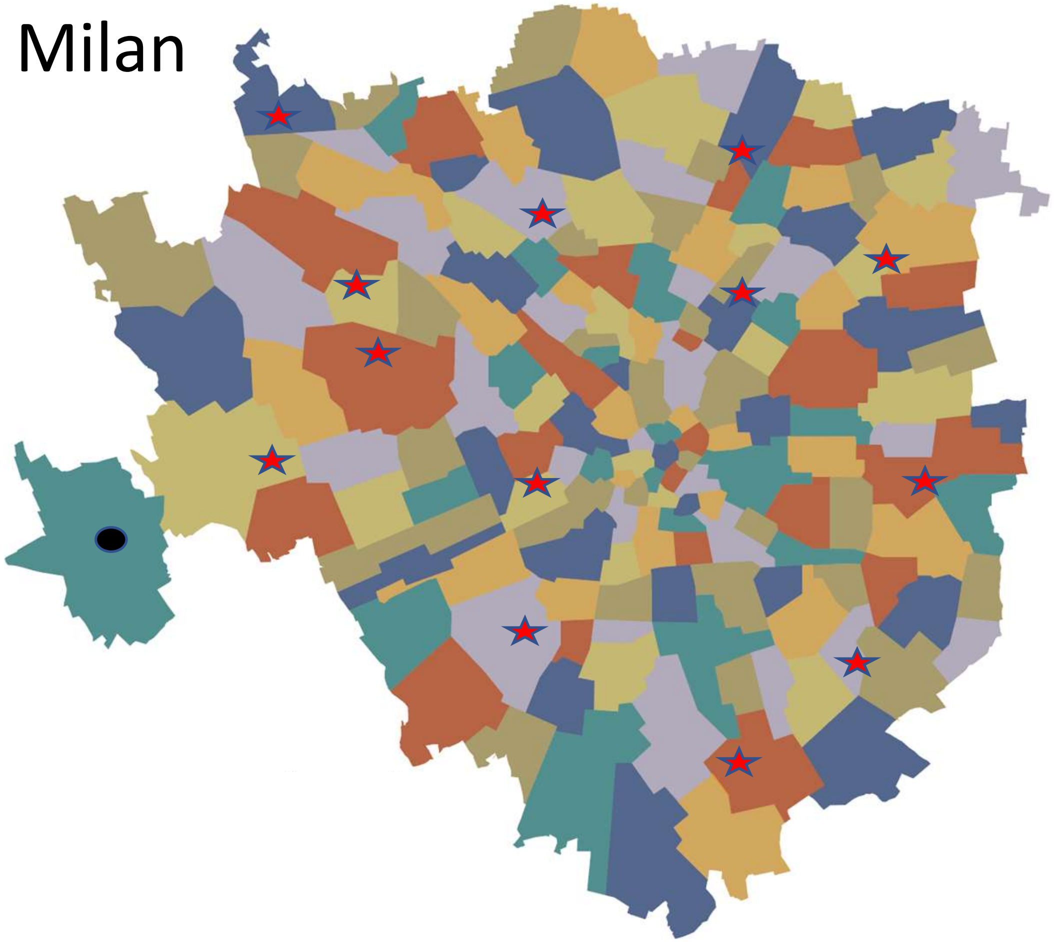
Output: Recharging points

Objectives: Cost and service to customers

Filippi, Guastaroba, Peirano, Speranza, TR C, 2023

The location problem

Milan



Demand of zone i
=
Number of vehicles in zone i
that request to be recharged

Graph

A single period model

$$[\text{SP-CFL}] \quad \min \quad \lambda \cdot \left(\frac{1}{\sum_{i\in\mathcal{I}} d_i} \sum_{i\in\mathcal{I}} d_i \sum_{j\in\mathcal{J}} c_{ij} \sum_{k\in\mathcal{K}} x_{ijk} \right) + (1-\lambda) \cdot \left(\sum_{j\in\mathcal{J}} F_j z_j + \sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} f_{jk} y_{jk} \right)$$

$$\text{s.t.} \quad y_{jk} \le u_{jk} z_j \quad j \in \mathcal{J}, k \in \mathcal{K}$$

$$\sum_{k\in\mathcal{K}} y_{jk} \le u_j z_j \quad j \in \mathcal{J}$$

$$\sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} x_{ijk} = 1 \quad i \in \mathcal{I}$$

$$\sum_{i\in\mathcal{I}} d_i x_{ijk} \le p_k y_{jk} \quad j \in \mathcal{J}, k \in \mathcal{K}$$

$$x_{ijk} \le y_{jk} \quad i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}$$

$$\sum_{j\in A_\ell} y_{jk} \ge \rho_{\ell k} \sum_{j\in A_\ell} \sum_{k\in\mathcal{K}} y_{jk} \quad k \in \mathcal{K}, \ell \in \mathcal{L}$$

$$z_j \in \{0,1\} \quad j \in \mathcal{J}; \quad y_{jk} \in \mathbb{Z}_+ \quad j \in \mathcal{J}, k \in \mathcal{K}; \quad x_{ijk} \in [0,1] \quad i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}.$$

Distance traveled by customers

Cost

Demand node

Location

Type of charger

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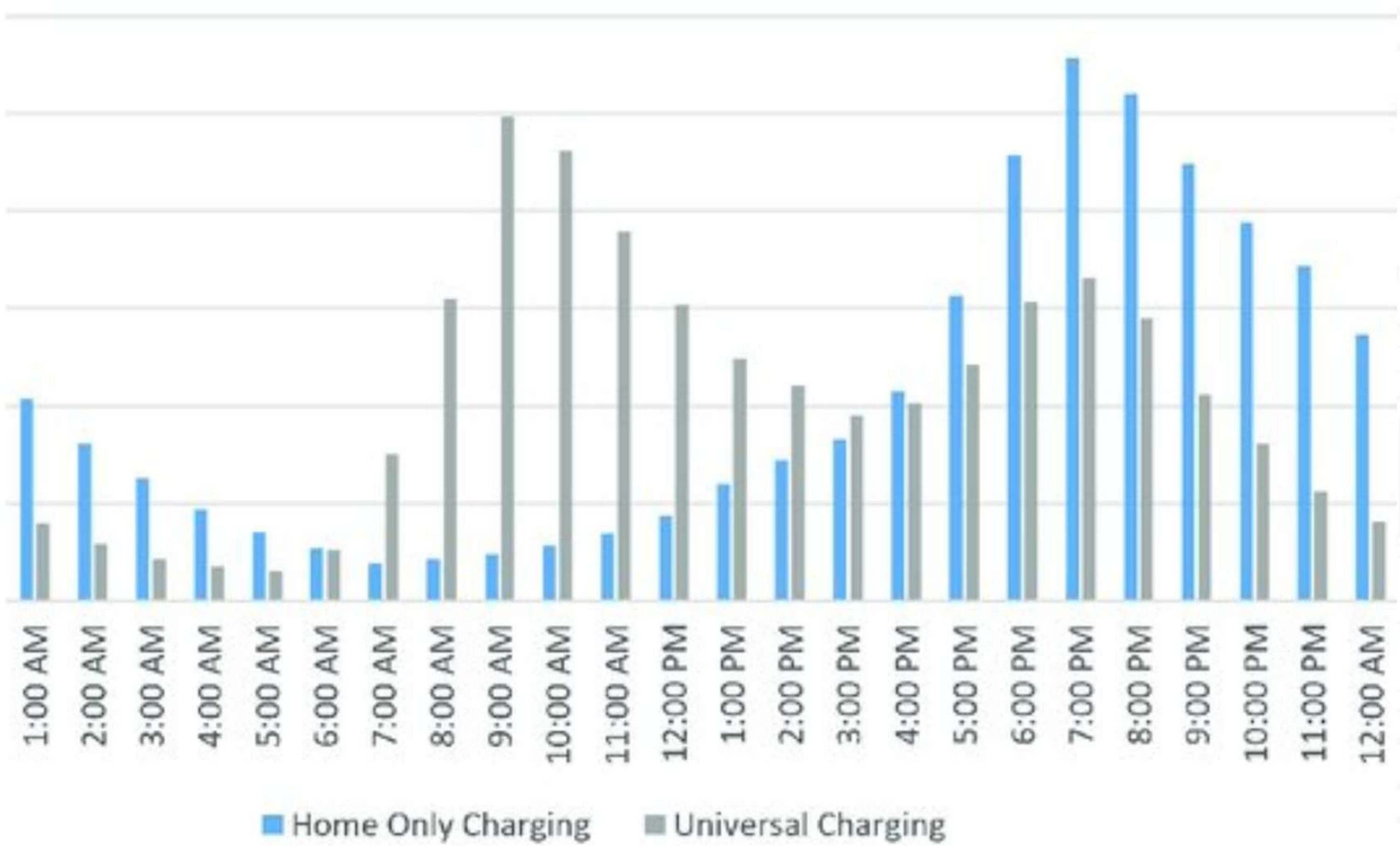
Variability of demand over time



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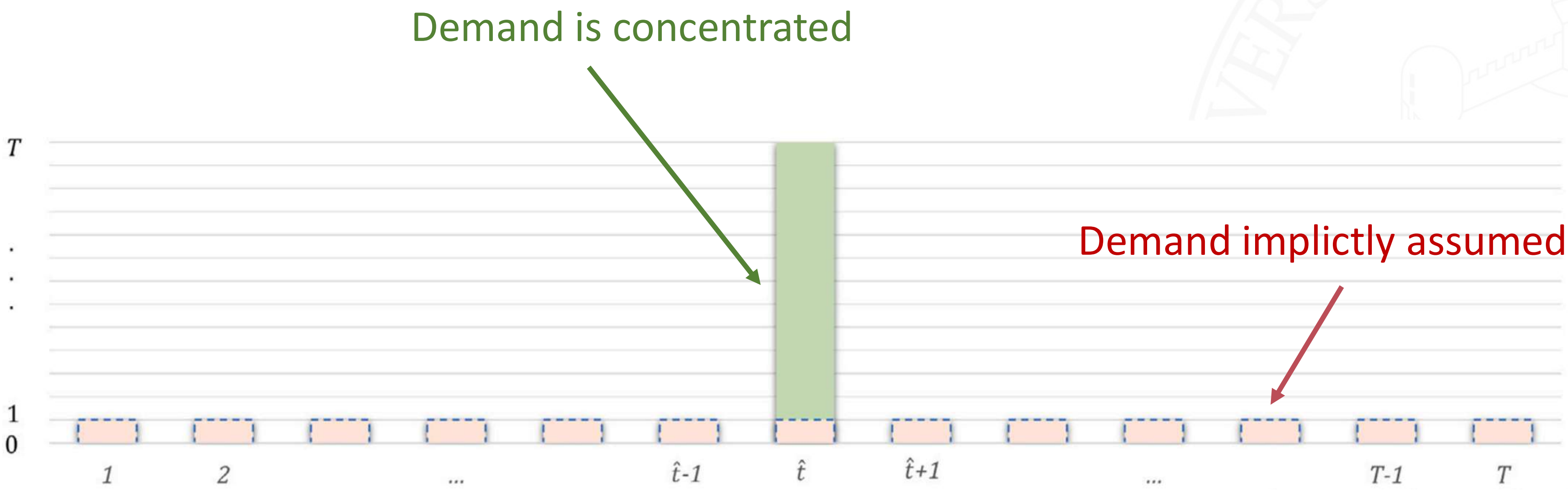
An extreme case

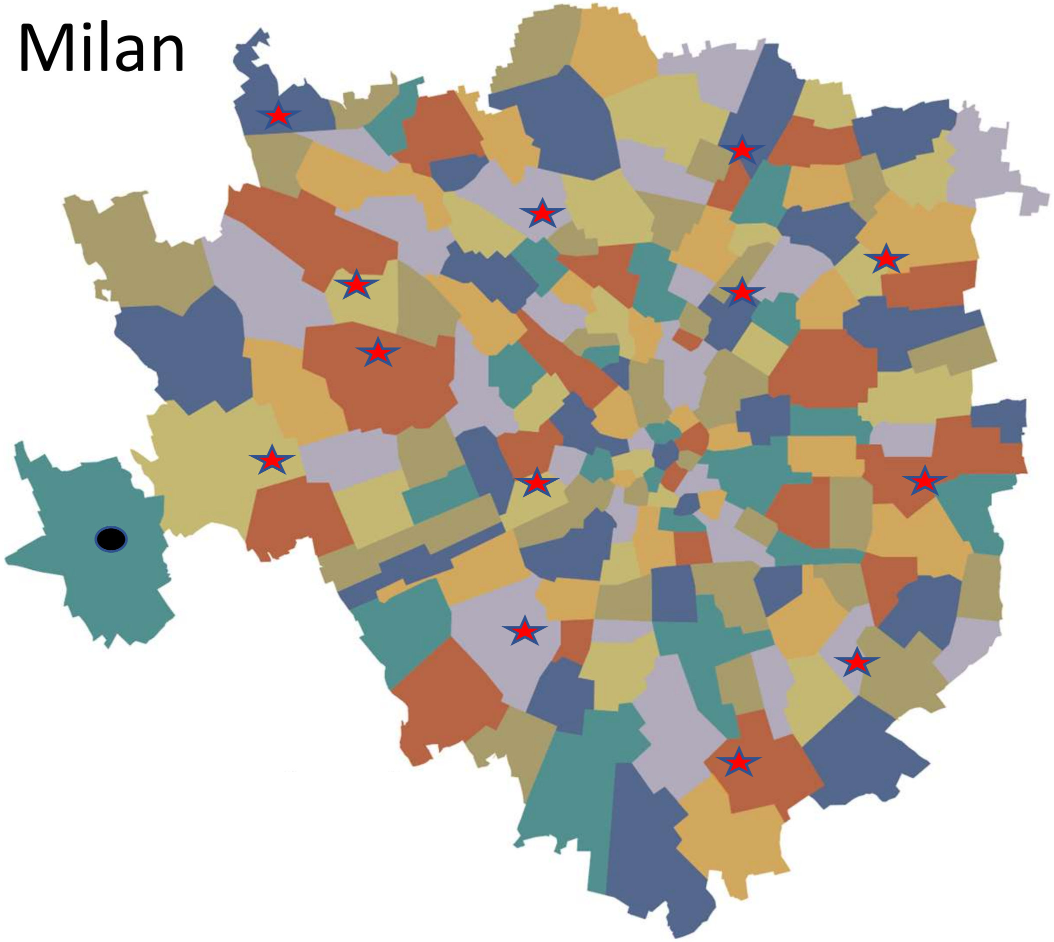
One time period = time needed to recharge one vehicle
Total demand over T time periods = T



Solution of a single period model: 1 recharging point

The location problem

Milan



Demand of zone i **at time t**

=

Number of vehicles in zone i that request to be recharged **at time t**

Graph

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A multi-period model

$$\min \quad \lambda \cdot \left(\frac{1}{\sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} d_i^t} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} d_i^t \sum_{j\in\mathcal{J}} c_{ij} \sum_{k\in\mathcal{K}} x_{ijk}^t \right) + (1-\lambda) \cdot \left(\sum_{j\in\mathcal{J}} F_j z_j + \sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} f_{jk} y_{jk} \right)$$

Distance traveled
by customers

Cost

Extension of constraints

Size of instances

I: The number of demand nodes = 50, 100, 150, 200, 250, 500

J: The number of potential locations = 10, 20, 30, 40, 50

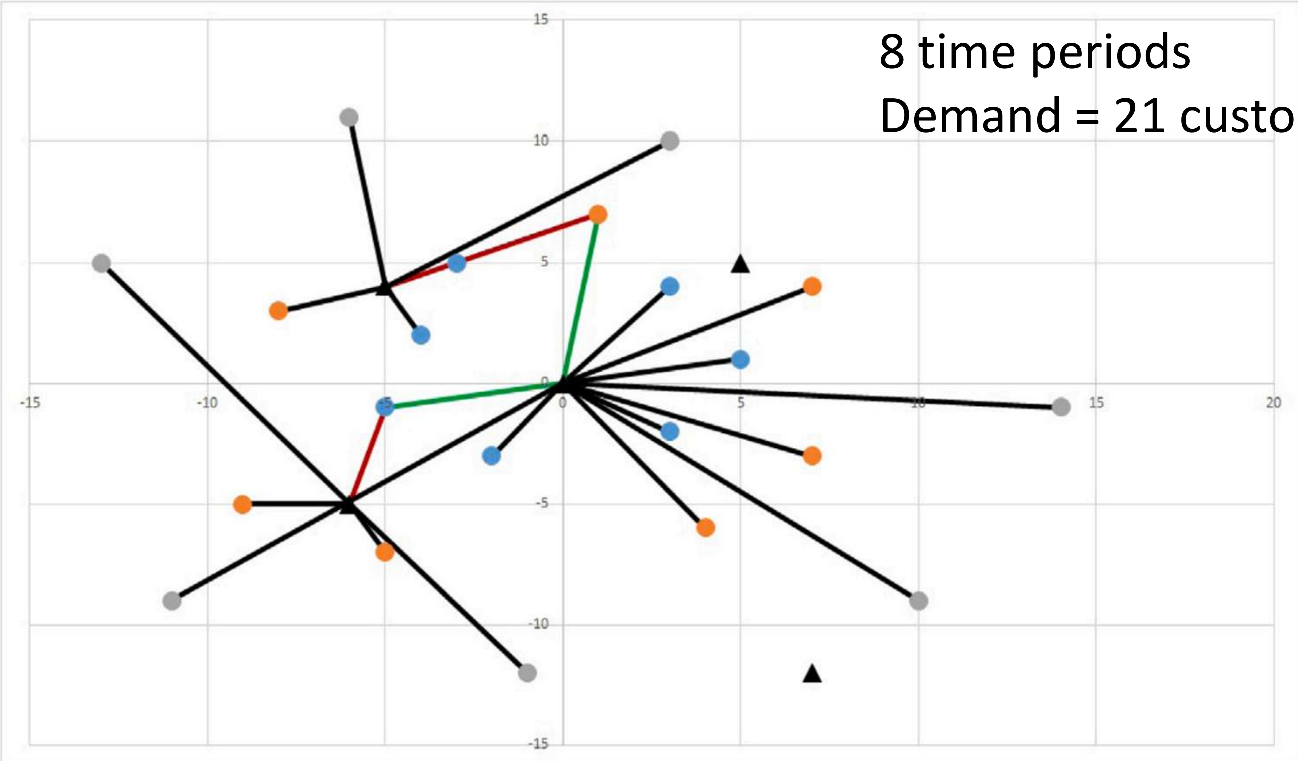
u: The maximum number of chargers to install in one station = 10, 20, 30

Single-period model: an example

100% of demand

67% of demand

33% of demand



3 over 5 recharging stations

17% of customers cannot be served

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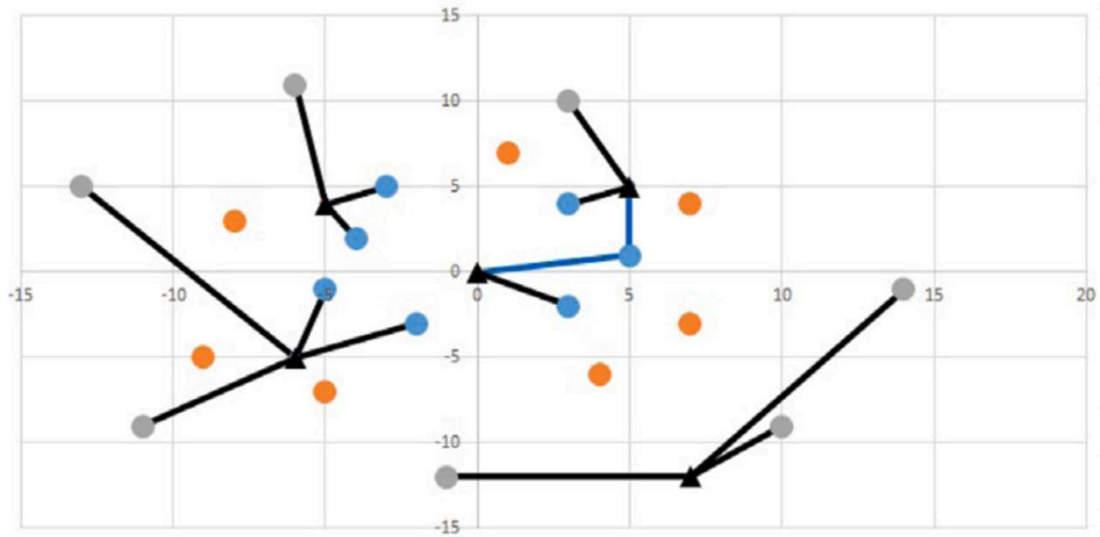
Multi-period model

100% of demand

50% of demand



5 recharging stations

All customers are served

A different assignment to recharging station for each time period t

Contribution:

A time-dependent location model for a new real problem

and computational results that show the value of the time-dependent model with respect to a known model

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<u>Sizing modular buses</u>:

a tactical optimization model for a new transportation system

M.Grazia Speranza

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Modular buses

Modular buses

Modules can be shared between lines (at predefined locations)
and be rebalanced (travel empty between stations)

Problem:
Min the number of modules necessary to satisfy the passenger demand
(as a secondary objective: min number of changes of line for passengers)

Filippi, Guastaroba, Peirano, Speranza, TR C, 2025

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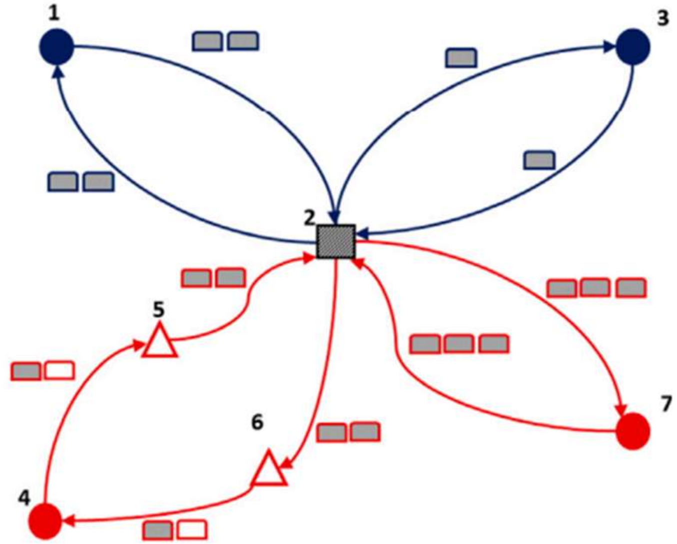
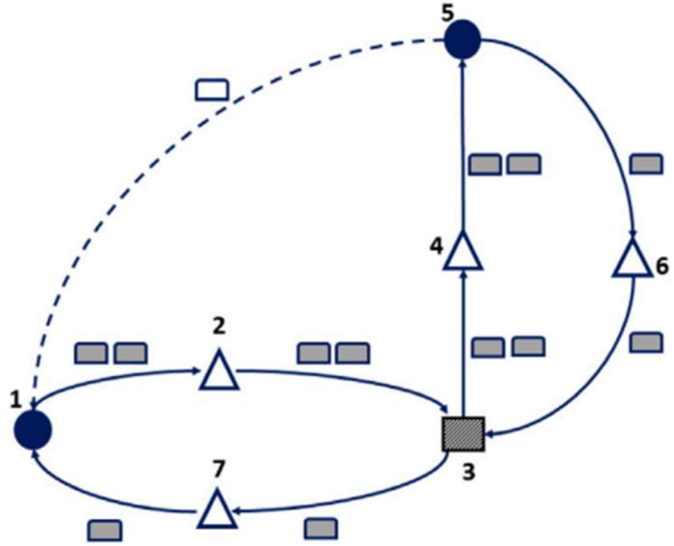
Modular buses

Modules are shared between lines





Modules are rebalanced

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Modular buses

The MILP model

$$\min \quad \sum_{\ell \in L} \sum_{h \in N_\ell} t'_{\ell h} \cdot w_{\ell h} + \sum_{(i,j) \in R} \tau_{ij} \cdot v_{ij} + \alpha \sum_{k \in K} \sum_{j \in J} p_k \cdot z_{kj}$$

$$\text{s.t.} \quad \sum_{\ell \in L} x_{kij\ell} = 1 \qquad k \in K, (i,j) \in P_k$$

$$x_{kij\ell} = x_{kjh\ell} \qquad k \in K, \ell \in L, (i,j,h) \in B_{\ell k} \mid j \in S$$

$$- z_{kj} \leq x_{kij\ell} - x_{kjh\ell} \leq z_{kj} \qquad k \in K, \ell \in L, (i,j,h) \in B_{\ell k} \mid j \in J$$

$$\sum_{k \in K} p_k \cdot x_{kij\ell} \leq Q \cdot w_{\ell h} \qquad \ell \in L, h \in N_\ell, (i,j,\ell) \in P_h^\ell$$

$$\sum_{P_h^\ell \in \Delta^-(j)} w_{\ell h} + \sum_{(i,j) \in R} v_{ij} = \sum_{P_h^\ell \in \Delta^+(j)} w_{\ell h} + \sum_{(j,i) \in R} v_{ji} \qquad j \in T \cup J$$

$$w_{\ell h} \in \mathbb{Z}_0^+ \qquad \ell \in L, h \in N_\ell$$

$$v_{ij} \in \mathbb{Z}_0^+ \qquad (i,j) \in R$$

$$x_{kij\ell} \in \{0,1\} \qquad k \in K, (i,j,\ell) \in A$$

$$z_{kj} \in \{0,1\} \qquad k \in K, j \in J.$$

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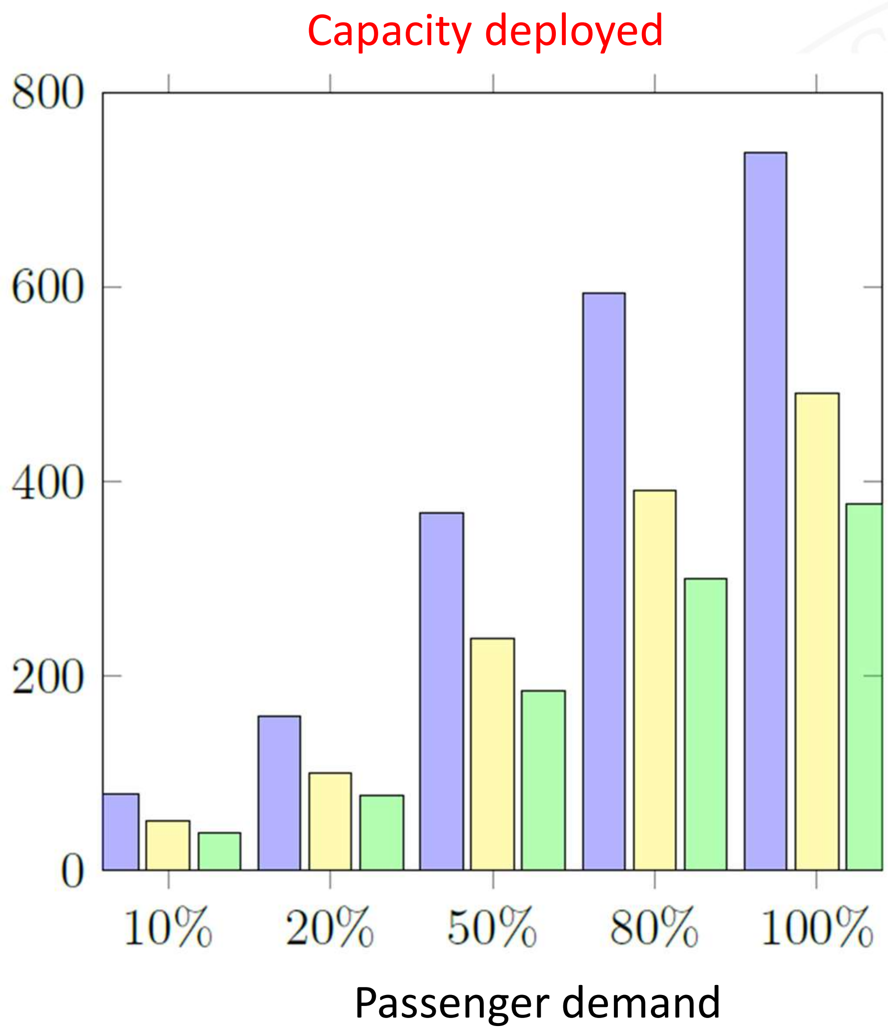
Modular buses

Fixed on a line (bus)

Modules are shared and rebalanced

m-rigid | m-flex(NR) | m-flex

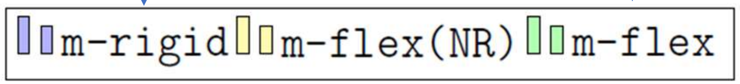
Modules are shared



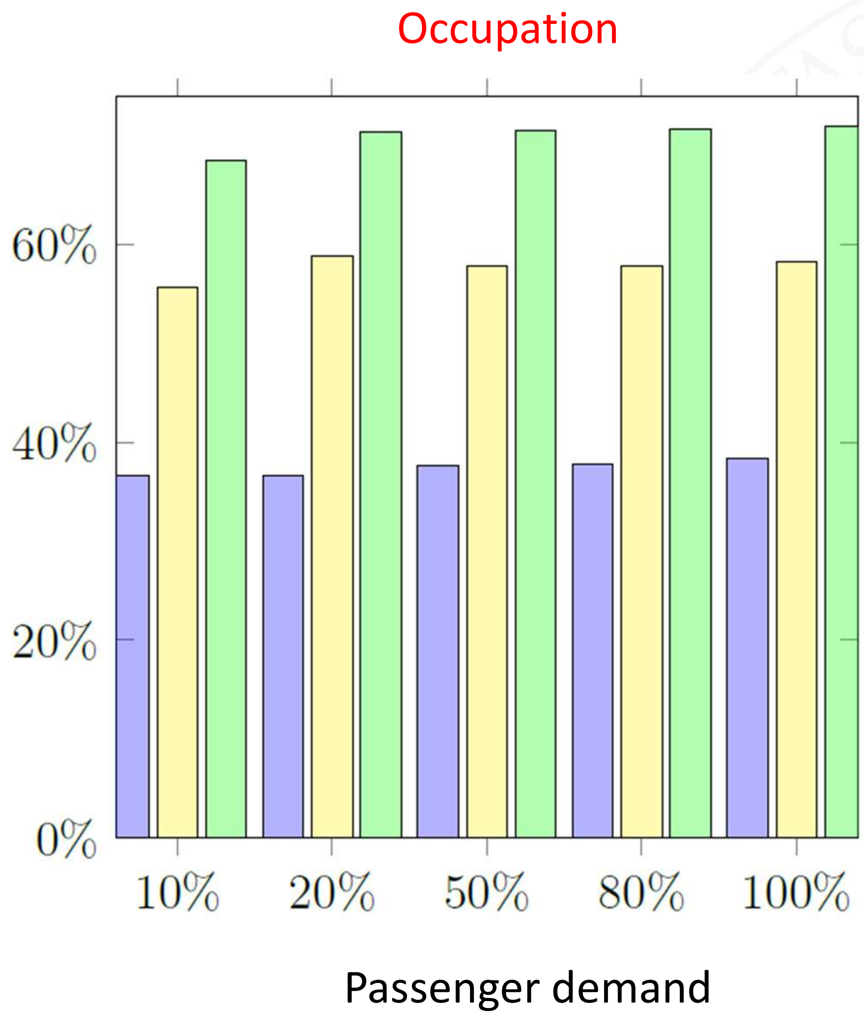
Modular buses

Fixed on a line (bus)

Modules are shared and rebalanced



Modules are shared



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Contribution:

An optimization model for a new real transportation system

and computational results that compare modular buses with traditional buses

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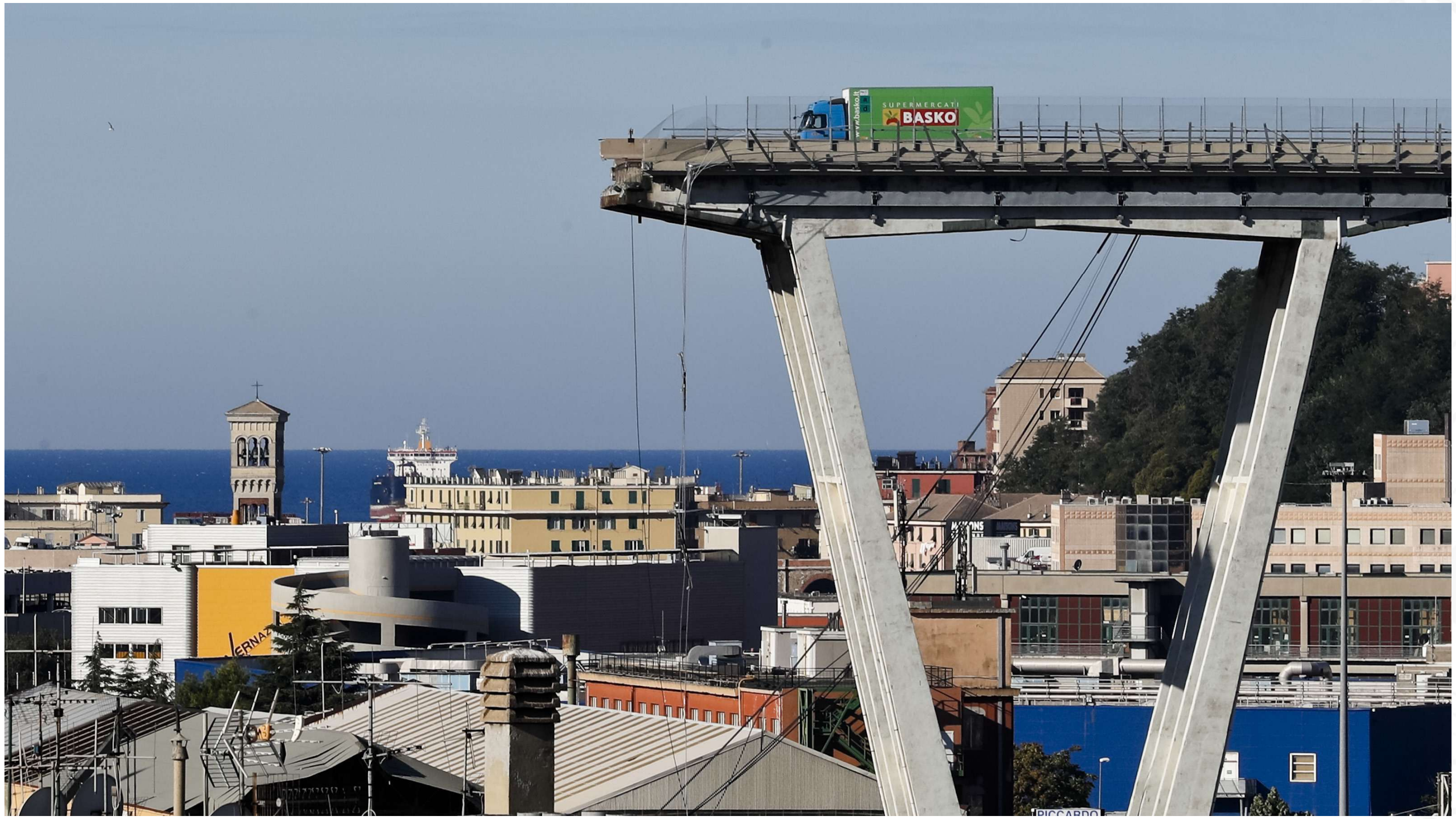
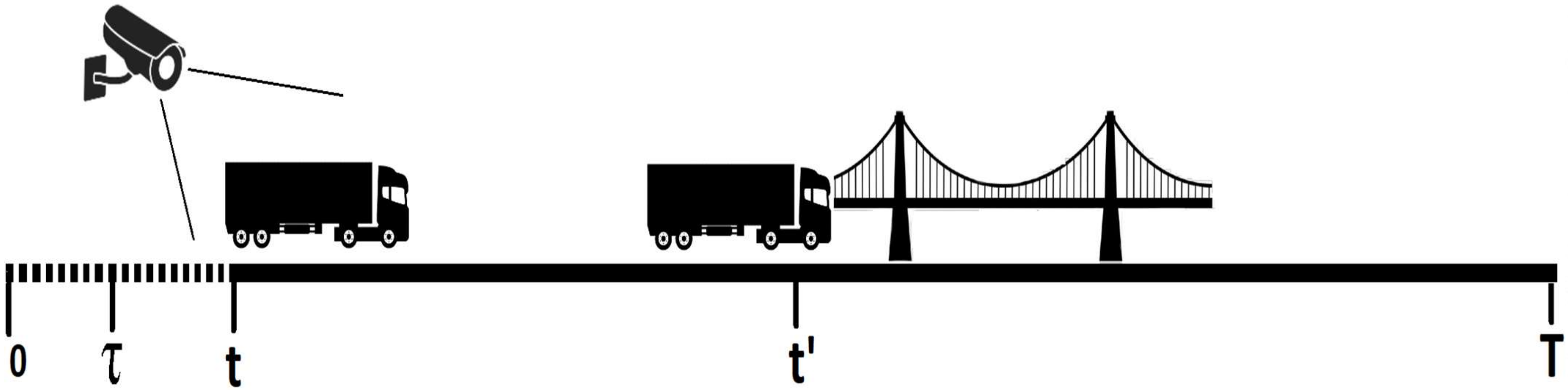
Rerouting of traffic:

Real-time traffic rerouting enabled by technological developments

Bridge monitoring and re-routing



Bridge monitoring and re-routing



Bridge monitoring and re-routing

Two optimization criteria:

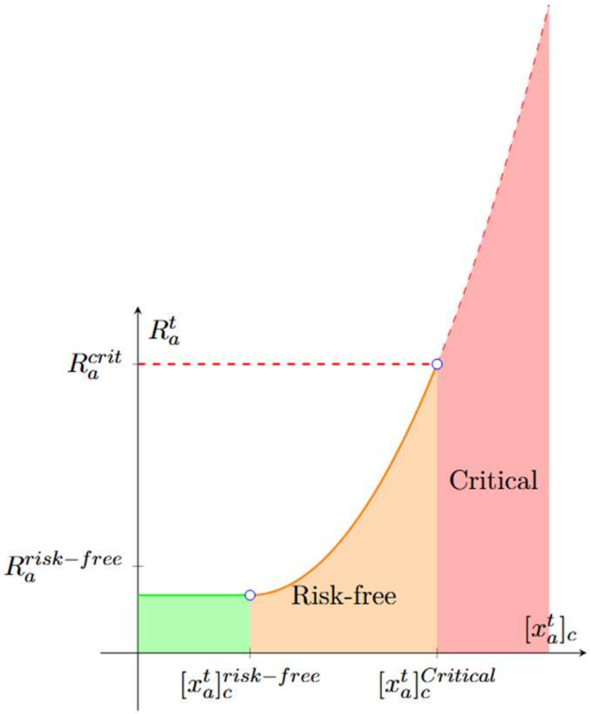
min risk of disruptions
min congestion in case of rerouting

Optimization model:

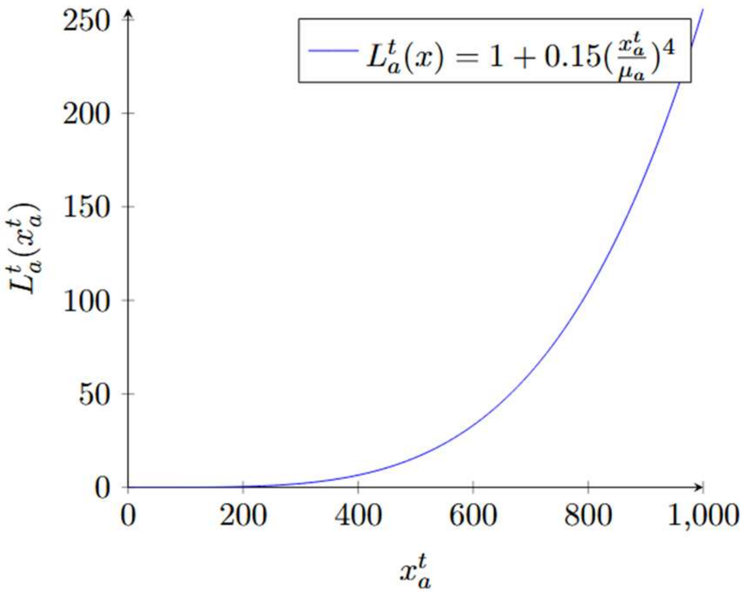
Min congestion measure
risk measure $\leq \rho$

Morandi, Peirano, Speranza, under revision, 2025

Bridge monitoring and re-routing



Risk-measure



Congestion-measure

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Bridge monitoring and re-routing

A bridge along Brescia's South Ring Road is a Case Study (about **34,000 veh/day per direction**).

2M+ vehicles sampled by a WIM system during a five-month monitoring period.
High percentages of overloaded vehicles were observed.

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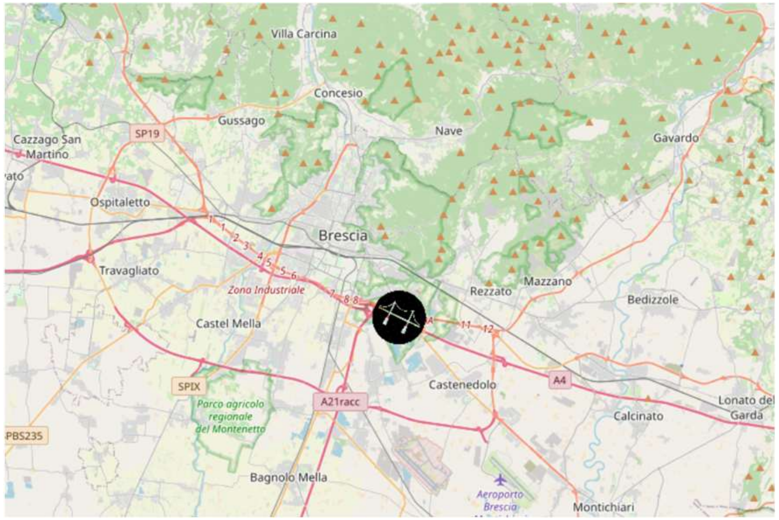
Bridge monitoring and re-routing



Road network extracted from osmnx

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Bridge monitoring and re-routing

In blue vehicles are allowed on the bridge
In the other colours alternative paths vehicles are rerouted to

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Contribution:

A real-time optimization framework for a real problem and computational results that show the value of the framework

Optimization
and
machine learning

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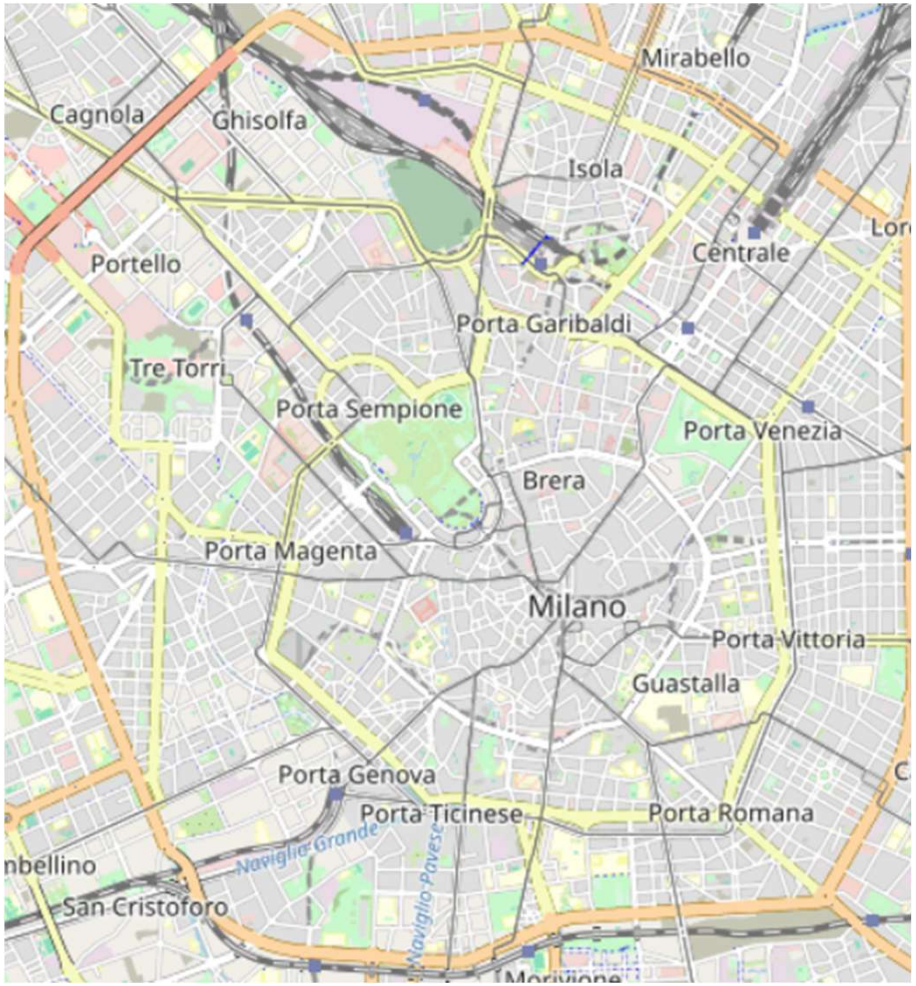
Real-time routing: on-going project




Thank you