ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
Department of Physics and Astronomy
Master's Degree in Applied Physics

Report for Complex Networks exam

Predicting *Zona30* policy impact in Bologna using a Complex Network based traffic simulation[1] [2]

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[1]Link to our Github repository

[2]Thanks to *Ufficio di statistica della Città metropolitana di Bologna* for providing us accidents data.

Contents

Abstract

Urban road structures are typical example of graphs, and their structure, topology and vulnerability can influence the car traffic flow through a city. In this report we investigate five urban networks using complex network algorithms. Four of them are from cities that adopted the *Zona30* speed limit system and the last one is from La Plata (Argentina), included to show the differences between self-made cities and a perfectly geometrical one.
Apart from Bologna, that is the first city in Italy adopting *Zona30*, we have chosen Nantes (France), Edinburgh (UK) and Zurich (Switzerland).

We also implemented an agent-based traffic simulation that uses complex network algorithms to compare the traffic flow statistics before and after the introduction of *Zona30*, only for the Bologna urban network, and to test if this simulation can predict the benefits of adopting such speed limits, such as a reduction of incidents and a more stable driving.
We quantified our simulation goodness using real traffic and accident data coming from *Comune di Bologna* e *quell'altro là, coso*, obtaining a minimum agreement with real data of 86.45%.

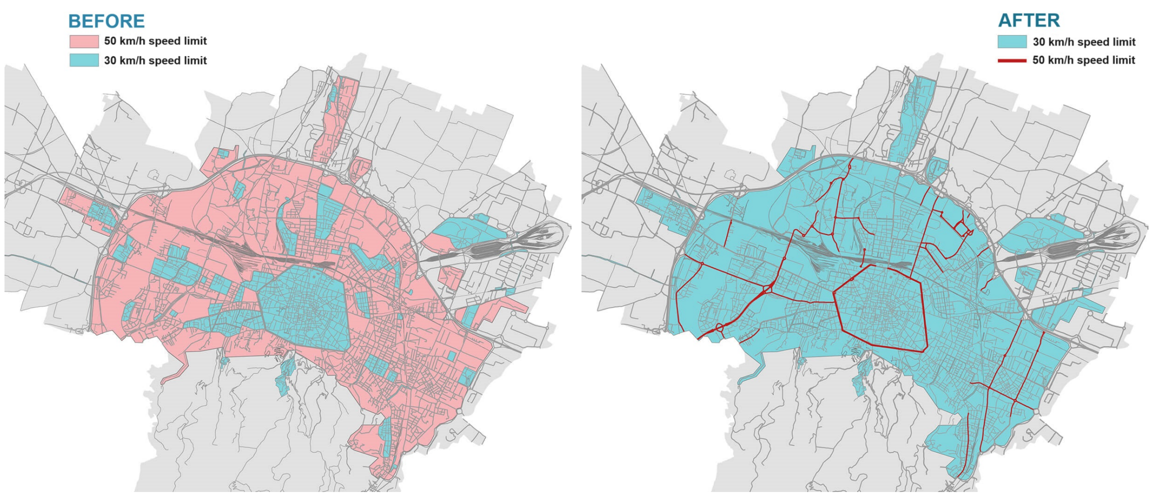
1 Introduction

The term *Zona30* is an expression referring to the speed limit of 30 $\frac{km}{h}$ within a city (with the exception of most relevant streets). Its purposes are to make traffic flow safer by decreasing the number of accident and more regular, avoiding wide oscillation in the accelerations, and to decrease the noise pollution.

Many cities worldwide [1] have already adopted *Zona30* and in several italian cities [2] is now under discussion. Bologna is the first city in Italy that adopted this speed limit system starting from January 2024 (see Figure 1).

The aim of this report is to compare the Bologna urban network properties with the ones from other cities that already adopted *Zona30* and to verify if a complex networks based algorithm could have been used to foresee the effect of adopting such speed limits. For the comparison we have chosen five cities: Bologna (Italy), Nantes (France), Edinburgh (Scotland), Zurich (Switzerland), La Plata (Argentina). Between those five only *La Plata* has no *Zona30* but we included it to see different behaviours between self organized cities and one who has a purely geometrical urban structure. See Figure 2 and 3 for a visual representation of those five urban networks we worked on.
We define and report also a vulnerability factor for the *Zona30* cities. This factor quantify the vulnerability of an urban network after removing some streets.

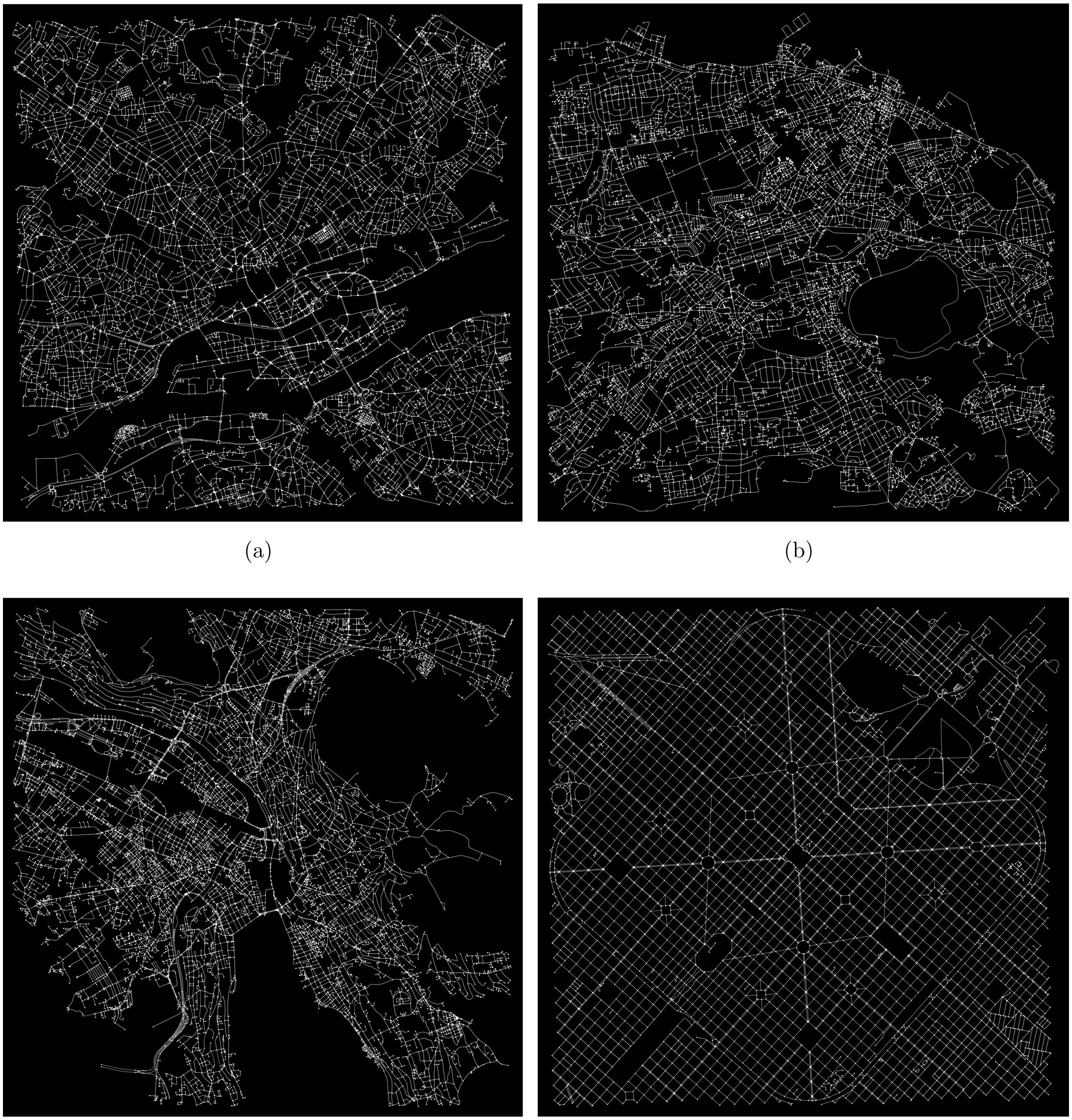
Lastly, we implemented an agent based traffic simulation in order to compare traffic flow statistics before and after the introduction of *Zona 30* policy. We verified the accuracy of our simulation by comparing its results with real traffic and accident data collected in the city.



(a) (b)

Figure 1: *Speed limits in Bologna before (a) and after (b) the introduction of the Zona30. Images from città30 website*

Figure 2: *Bologna* $50km^2$ *urban network.*



(a) (b) (c) (d)

Figure 3: $50km^2$ *urban networks:* ***a)*** *Nantes (France),* ***b)*** *Edinburgh (UK),* ***c)*** *Zurich (Switzerland),* ***d)*** *La Plata (Argentina)*

2 Background

2.1 Complex Networks theory

2.1.1 Connectivity

To perform a descriptive analysis of an urban network, apart from number of nodes and edges, we take in consideration the following factors:

- **Alpha coefficient** (Lin and Ban 2017 [3]): Also called *meshedness coefficient*, is used to measure the structure of cycles in a planar system:

$$\alpha = \frac{N_E - N_V + 1}{2 \cdot N_V - 5} \tag{1}$$

  Where N_E and N_V are number of edges and number of nodes. According to the Euler's formula, the number of cells in a planar network can be calculated as $N_E - N_V + 1$, and the maximum number of cells in a network equals $2 \cdot N_V - 5$. In this case, the alpha coefficient can be seen as the ratio of the real number of cells and the maximum number of cells in a network. Therefore, the value of the alpha coefficient lies in the range between 0 and 1.

- **Beta coefficient** (Lin and Ban 2017 [3]): It's simply the ratio between the number of edges and number of nodes of a network. It measures the connectivity of a network, and a larger value indicates a better connectivity:

$$\beta = \frac{N_E}{N_V} \tag{2}$$

- **Gamma index** (Lin and Ban 2017 [3]): It's a measure of the relation between the real number of edges and the number of all possible edges in a network:

$$\gamma = \frac{N_E}{(3 \cdot N_V - 2)} \tag{3}$$

- **Average Path Length** (Lin and Ban 2017 [3]): Reflects the internal structure of a network by containing the internal separations of all nodes:

$$L = \frac{1}{N_V \cdot (N_V - 1)} \sum_{i>j} d_{ij} \tag{4}$$

  Where d_{ij} is the shortest path length bewteen node i and j.

- **Global efficiency**(Porta et al. 2006 [4]): A measure of how efficiently information is exchanged across the entire network. It quantifies the parallel communication between all pairs of nodes in the network.

$$E(G) = \frac{1}{N_V(N_V - 1)} \Sigma_{i>j \in G} \frac{1}{d_{ij}} \tag{5}$$

  with G neural network and d_{ij} is again the shortest path length between nodes i and j.

Global efficiency is inversely related to the topological distance between nodes: more distant nodes have less efficient communication.
In practical terms for an urban network, this concept reflects how easy it is for vehicles to reach their destinations across the road network as a whole.

2.1.2 Centralities

Centrality measurements commonly used in complex networks include degree centrality, betweenness centrality and closeness centrality.
They provide insights into different aspects of network structure and node importance based on various criteria, such as node connectivity, proximity to other nodes, influence within the network, and global network structure. Each of these centrality measures contributes to a comprehensive understanding of network dynamics and node importance [5].

- **Edge betweenness centrality**: Quantifies the importance of an edge based on its role in the shortest paths between nodes, acting as a "bridge" in the network.

$$C_i^{EB} = \frac{1}{(N_V - 1)(N_V - 2)} \sum_{j,k \in V; j \neq h} \frac{n_{jh}(i)}{n_{jh}} \quad (6)$$

$n_{jh}(i)$ number of the shortest path between node j and h, passing through edge i
n_{jh} total number of shortest paths between j and h
N_V number of nodes in network V

Edges with high edge betweenness centrality act as crucial "bridges" in the network, controlling the flow of information.

- **Degree centrality**: In a complex network, degree centrality reflects the number of neighbors a node has, indicating its level of influence within the network.
This measure is particularly relevant in urban street networks, where nodes represent intersections and edges represent streets so it helps to identify crucial intersections that serve as key points for traffic flow and connectivity.

$$C_i^D = \sum_{j \in V; i \neq j} a_{ij} \quad (7)$$

$a_{jh}(i)$ entry value in the adjacency matrix

The adjacency matrix is a square matrix used to represent the connections between nodes in a graph, where the rows and columns represent the vertices of a graph.
Each entry in the matrix indicates whether there is a direct connection (edge) between two vertices i and j: if the connection exist the value in the matrix at the i-th row and j-th column is 1, otherwise, it is 0.

- **Closeness Centrality**: Quantifies how close a node is to all other nodes in the network: as high is the closeness centrality value as more "central" is the node, which means that it can quickly interact with all other nodes in the network [6].
Nodes with high closeness centrality can spread information efficiently across the network.

$$C_i^C = \frac{(N_V - 1)}{\sum_{j \in V; i \neq j} d_{jh}} \quad (8)$$

d_{jh} shortest path between node i and j, passing through node i
N_V number of nodes

- **Information Centrality** (Porta et al. 2006 [4]): It follows from the definition of the global efficiency and quantifies the importance of a node based on the information it holds or processes within the network.
  It is calculated as the difference in network efficiency before and after the removal of the node, reflecting how communication over the network is affected by deactivating that specific node:

  $$C_i^I = \frac{E(G) - E(G')}{E(G)} \qquad (9)$$

  $E(G)$ and $E(G')$: global efficiencies before and after removing the i^{th} node

  The computation involves analyzing the flow of information through each node, considering factors such as the volume of information passing through the node and the impact of that information on the whole network.
  Nodes with high Information Centrality are an essential components for efficient information propagation within the network.

2.1.3 Vulnerability

To assess the vulnerability of an urban network, we adopt a modified approach to computing information centrality. Instead of removing individual nodes one by one, we selectively remove one or more edges, which effectively eliminates multiple nodes simultaneously. By comparing the global efficiencies of the resulting graph with the original network, we can quantify the network's vulnerability to disruptions.

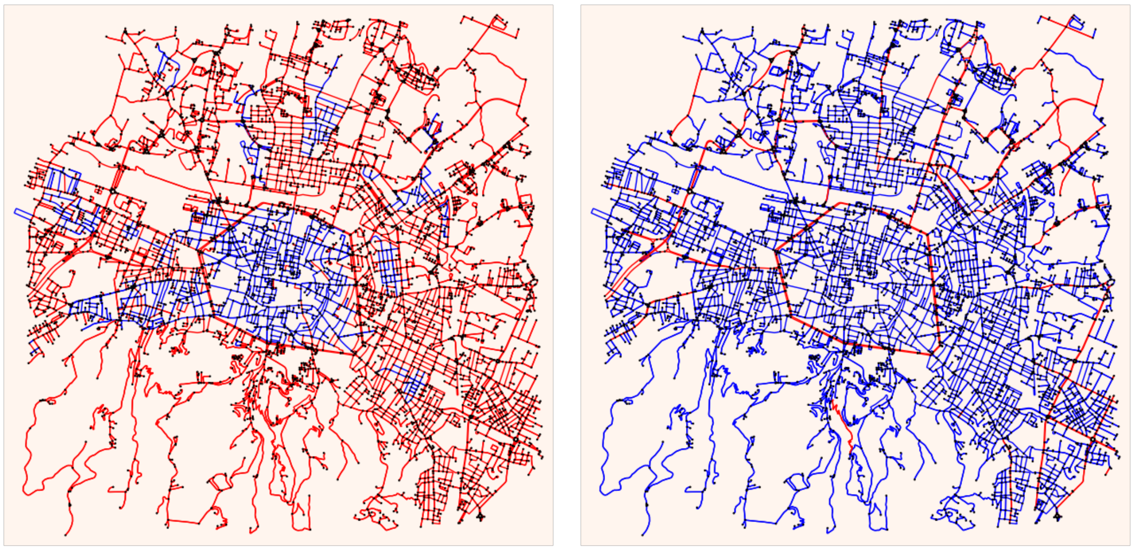
$$\text{Vulnerbility} = \frac{E(G) - E(\overline{G})}{E(G)} \qquad (10)$$

Where $E(G)$ is the original graph global efficiency and $E(\overline{G})$ is the global efficiency after removing several nodes.
After such operation we end up with a single value that increases when the shortest path lengths increase after removing some edges. An higher values corresponds then to a more vulnerable network.

2.2 Simulation

We designed a traffic simulation, written in Python, that is designed on the Bologna urban network structure, interpreting edges as streets and nodes as crossings. Its aim is to study the traffic flow and accident positions after the introduction of *Zona30* and also to compare the outcomes with a simulation based on the previous speed limit conditions, referred to as *Città50* in this study (see Figure 4).
The simulation involves the movement of 3000 cars along the network edges, interacting with each other.
We sampled the ending node of a car path from a probability distribution that mimics the Closeness Centrality, in order increase the probability to have a target node within the city center. The starting node was selected from the inverse of the Closeness Centrality distribution (see Figure 5).
The path is generated computing the shortest path between the first and the last node using the OSMnx built-in function *ox.shortest_path(graph,origin,destination,weight)*

weighted to minimizing the travel time, since our purpose is to compare results with different speed limits. To visualize and highlight the most trafficked roads, every time a car travel through an edge, its *'passage'* value increments by one unit.



(a) *Città50* (b) *Zona30*

Figure 4: *Speed limits used in the simulation for the two scenarios: red 50km/h and blue 30 km/h.*

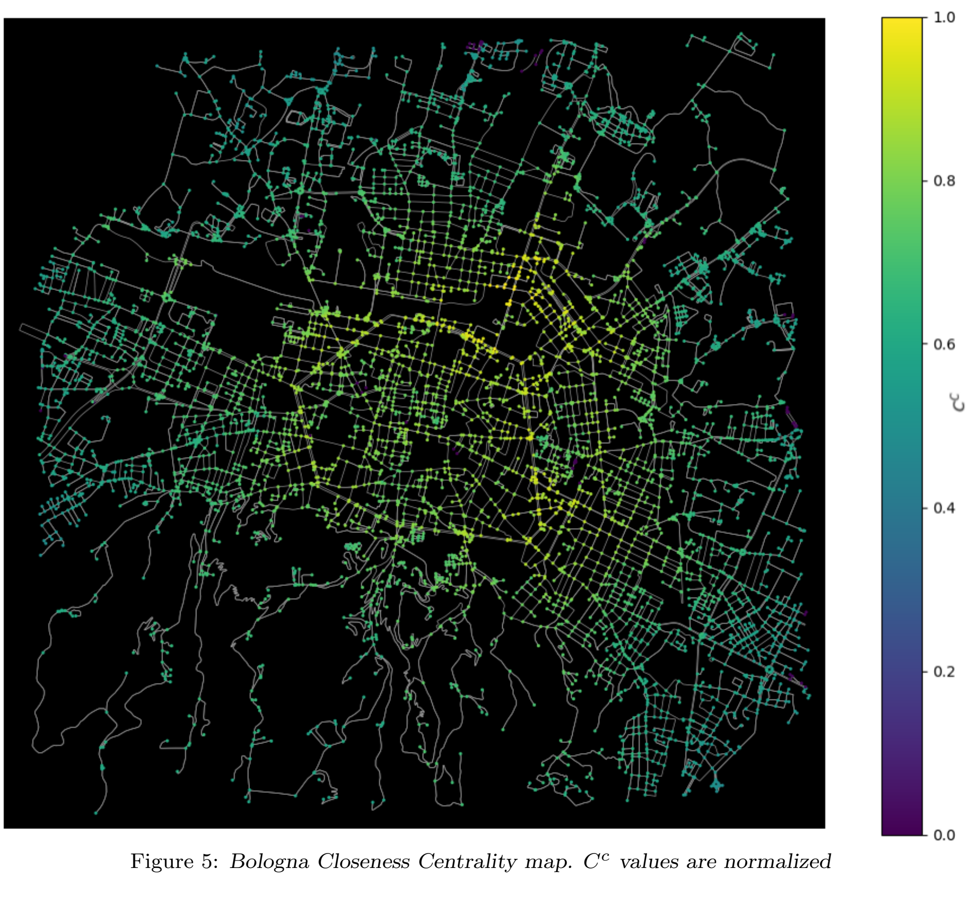


Figure 5: *Bologna Closeness Centrality map. C^c values are normalized*

The initial velocity of each car is determined by the speed limit of the first road it enters, with the initial velocity vector's magnitude randomly chosen from a uniform distribution that spans from $max\_speed/4$ to maximum speed, and its direction pointing towards the next node.
When a car reaches its destination it simply starts again a new path from another node.

To improve the realism of the simulation, the acceleration, or deceleration, for each vehicle is computed considering the distance from the next node along the path and the presence of other vehicles nearby. The accident physics is purely stochastic, it depends only on the relative speeds of two cars, on their relative distance and direction. Figure 6 shows the probability distribution with which an accident can occur and in order to have a non-linear behaviour, it's derived from the logistic function:

$$accident\_pdf(x) = 2 \cdot \frac{0.01}{0.01 + e^{-x \cdot \frac{2}{100}}} [\%] \tag{11}$$

Every time an accident occurs in a certain point of the map, the nearest node attribute *'accident'* increases by one unit, so that we can show the map of the accident positions.

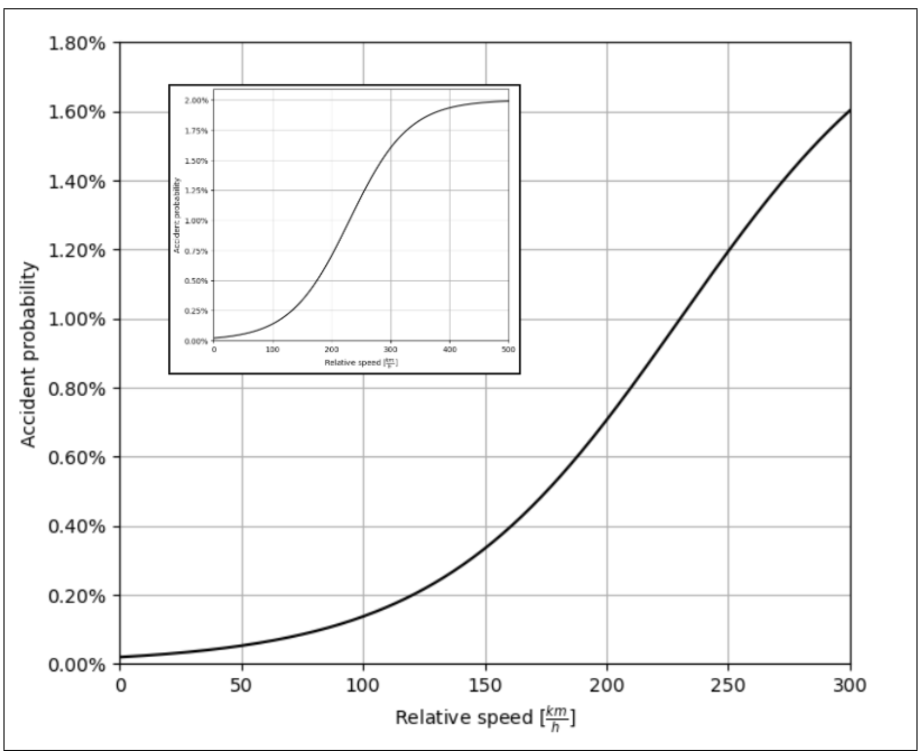


Figure 6: *Accident probability distribution for relative speeds between 0 and 300* $\frac{km}{h}$*. At the top left of the figure the complete sigmoid, which has its maximum at 2%. In our simulation the relative speed should never exceed 100*$\frac{km}{h}$*.*

3 Analysis and Results

3.1 Datasets

3.1.1 OSMnx

Two key Python libraries were used to acquire and analyze data for the five selected cities OSMnx [7] and NetworkX. In combination, these libraries offer a powerful set of tools for studying and visualizing street networks and other spatial networks:

- OSMnx is a specialized library for working with geospatial data from OpenStreetMap
- NetworkX is a more general-purpose library for network analysis, enabling the creation, manipulation, and examination of the structure and dynamics of complex networks.

The urban networks of Bologna, Nantes, Edinburgh, Zurich and La Plata were loaded using OSMnx, as it allows generating them at any desired scale by adjusting the distance from the city center. This can be done with the built-in function *osmnx.graph_from_point((lat,long),dist)*, which also provides valuable data such as street names, speed limits and travel times.

3.1.2 Bologna public data

Traffic data for 2023 and 2024 were obtained from the *Comune di Bologna* website [8]. These data represent the number of vehicles detected passing through streets across the entire Comune area over the course of a full year, with the exception of 2024 which covers approximately four months. Latitude and longitude coordinates were used to identify street locations, as OSMnx occasionally lacks complete street name data.

Accident data were retrieved from the Monitoraggio Incidenti Stradali [9] (Road Accident Monitoring) database, but are limited to the 2010-2022 time period, precluding comparison with the *Zona30* accident simulation. The accident data include the location of each incident in UTMRER coordinates and cover a $28km^2$ area.

3.2 Urban networks analysis

3.2.1 Connectivity analysis

The connectivity coefficients computed for each city are presented in Table 1.
Bologna exhibits the lowest alpha coefficient and gamma index among the cities analyzed. This suggests that Bologna's urban network is less cyclical and less complex compared to the other cities, indicating potential for improvement in terms of maximizing possible connections within the network.
Despite its beta coefficient is slightly lower than the other cities, a value of $\beta = 1.99$ still reflects a good level of network connectivity and efficiency.
A beta coefficient close to 2 is a sign of an efficient and well-connected network, as it means there are enough links to allow for multiple paths between nodes. [10][11][12]

La Plata has the lowest Average Path Length, more than 100 m lower compared to all other cities, because of its intrinsic efficiency, due to its particular geometric design.

Connectivity Coefficients						
City	**# Nodes**	**# Edges**	**Alpha**	**Beta**	**Gamma**	**APL**
Bologna	6176	12284	0.49	1.99	0.66	895 m
Nantes	9981	21670	0.59	2.17	0.72	796 m
Edinburgh	10323	23030	0.62	2.23	0.74	835 m
Zurich	9600	20874	0.59	2.17	0.72	809 m
La Plata	4362	9169	0.55	2.10	0.70	674 m

Table 1: *Connectivity analysis coefficients for cities in a 50km^2 area, with a special consideration for La Plata's 34 km^2 geometric nature. APL (Average Path Length) values are calculated over a 3.8 km^2 area to optimize computational time costs*

3.2.2 Centrality analysis

In this section we present an analysis based on three centralities measure, underlying different aspect of each of those five cities. Every centrality computation is done using the corresponding Networkx built-in function.

Edge Betweenness centrality distributions

C^{EB} is a critical measure for assessing the robustness of a network, i.e. its ability to maintain connectivity and function despite failures or attacks. A network where most edges have low C^{EB} values have few edges as critical bridges. Viceversa if many edges have significant C^{EB} values there is a more dispersed distribution of critical paths across the network. The Bologna C^{EB} map can be seen in Figure 7, those of other cities are uploaded on our Github repository.

Following the centralities analysis from Shang et al. 2019 [13] we plotted the Complementary Cumulative distributions (CCD) for C^{EB} values (Figure 8), and we fitted them with an exponential function $\propto e^{-\lambda \cdot x}$. In Table 2 we report the results of the fits. Lower value of λ indicates a slower decay, implying that high C^{EB} values are more common. This suggests that the network may be more vulnerable, as many edges play crucial roles in shortest paths.
The C^{EB} CCDs for those five cities exhibit distinct patterns:

- Nantes and Bologna show slow declines in the CCD curve compared to other cities (low values of λ) , indicating a significant proportion of edges with relatively high C^{EB}. Nantes, in particular, exhibits the slowest decline for highest values. This implies that a larger number of edges in Nantes are crucial for traffic flow.

- Zurich and Edinburgh curves show less high values of C^{EB}. This could imply a more uniform traffic network where multiple edges share the centrality load.

- La Plata has the steepest decline among the cities, with a significant drop in the CCD at lower C^{EB} values. This indicates that La Plata's traffic network relies heavily on a few highly central edges.

The results highlight how cities like Nantes and Bologna, with their slower CCD decline, may have certain critical edges that, if disrupted, could significantly affect overall traffic flow. In contrast, cities like Zurich, Edinburgh and, in particular, La Plata, may have a more resilient network structure.

Figure 7: *Bologna Edge Betweenness centrality map.*

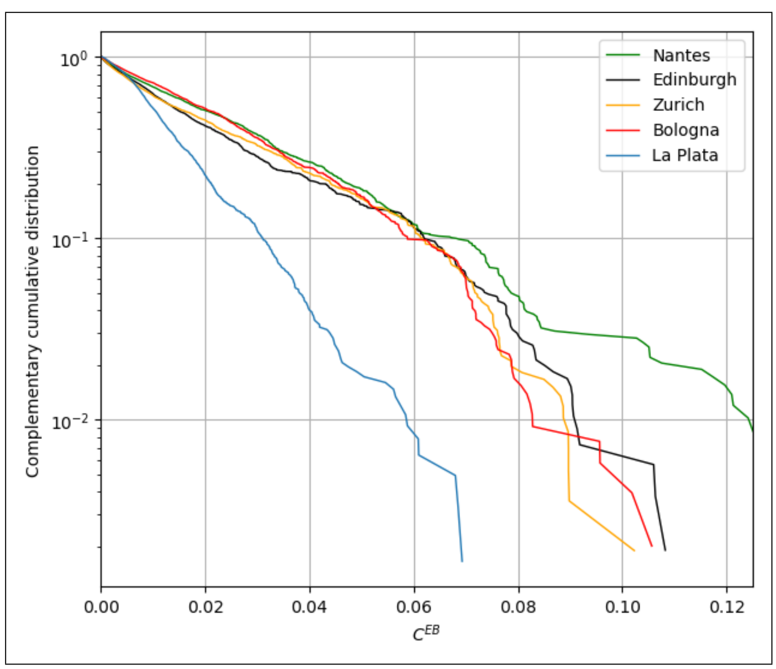


Figure 8: *Complementary cumulative distribution of edge betweenness centrality C^{BC}, in semi-logarithmic scale, for Nantes, Edinburgh, Zurich, Bologna, and La Plata traffic networks.*

Edge Betweenesses centrality fit values		
City	λ	R^2
Bologna	34.29	0.99
Nantes	36.21	0.99
Edinburgh	45.47	0.99
Zurich	45.86	0.98
La Plata	65.69	0.98

Table 2: *Results of an exponential fitting of C^{EB} values from Figure 8 and corresponding R^2 values.*

Degree centrality

Degree centrality provides insights into the connectivity of nodes within a network, indicating how well-connected individual intersections or junctions are. The Bologna C^D map can be seen in Figure 9, those of other cities are uploaded on our Github repository.

Degree centrality was calculated for each node in the networks and the degree centrality distributions for the five cities are shown in Figure 10.

- Edinburgh and Zurich show two prominent peaks at degrees 2 and 6, with the highest percentage of nodes at degree 6. That suggests a network structure with central nodes that serve as hubs for the less connected nodes.

- Nantes and Bologna present a flatter distribution with one peak at 6 and high percentage of nodes between degrees 2 and 4. This indicates a balanced connectivity where nodes have a moderate number of connections and so they are neither highly central nor isolate.

- La Plata stands out with a pronounced peak at degree 4, where over 50% of nodes have exactly 4 connections. This indicates a highly regular network structure with most nodes having the same degree of connectivity.

Cities like Edinburgh, with its high degree centrality nodes, may have critical intersections that play a crucial role in facilitating traffic flow within the city, where traffic converges and disperses.

In contrast, La Plata's regular degree distribution implies a balanced distribution of connections across nodes suggesting a more predictable and resilient network structure.

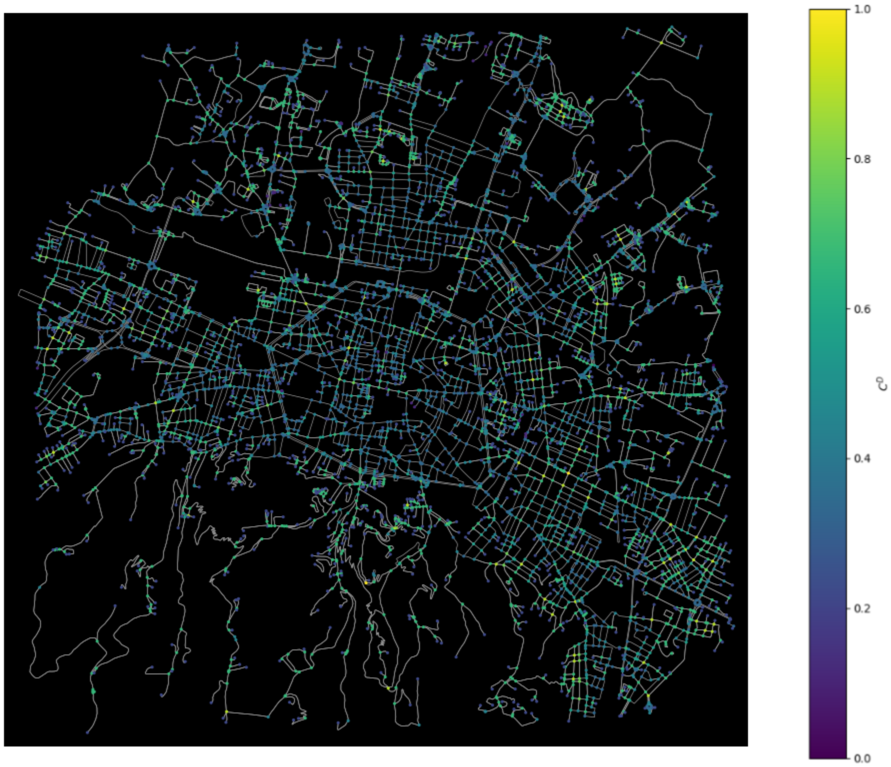


Figure 9: *Bologna Degree Centrality map.*

Closeness centrality

Closeness centrality C^c offers insights into how quickly information or traffic can spread from a node to all other nodes, indicating the efficiency of the network. The Bologna C^c map can be seen in Figure 5, those of other cities are uploaded on our Github repository.

A higher closeness centrality means that the average distance to all other nodes is shorter and this implies shorter travel times and distances for vehicles, which translates to higher efficiency.

High closeness centrality implies better accessibility of nodes, which means that any location can be reached more easily and quickly from any other location.

Also, it is less probable to have bottlenecks because traffic can disperse more evenly across the network, increasing the overall efficiency. Closeness centrality was calculated for each node in the network, and the results are presented in Figure 11 as the percentage of nodes (Counts [%]) versus their corresponding C^c values.

In particular Nantes (in green) has a peak around C^c of 0.015, indicating a relatively concentrated distribution of proximity centrality.

Edinburgh (in black) and Bologna (in red) show similar distributions, with peaks around 0.017 and 0.018 respectively, suggesting a high percentage of nodes in these cities reach a similar level of closeness efficiency. Zurich (in orange) has a wider distribution with a slightly higher peak compared to Bologna, but La Plata (in blue) presents a significantly different distribution, with a peak extending between 0.022 and 0.030. These results indicate a significant variation in network efficiency among the cities, with La Plata showing flatter distribution and greater centrality values compared to the other analyzed cities.

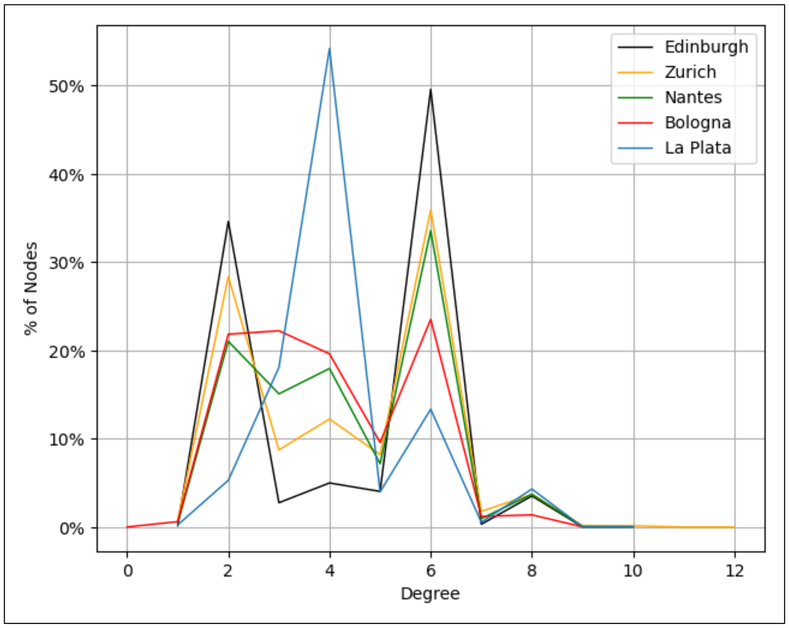


Figure 10: *Distribution of degree centrality for the traffic networks of Edinburgh, Zurich, Nantes, Bologna, and La Plata.*

High values of closeness centrality indicate that nodes can reach each other quickly, implying short path lengths between nodes (La Plata has also the shortest APL among the considered cities, see Table 1). The flatness of the distribution indicates that this high accessibility is consistent across the network, with most nodes having similar centrality values. Therefore, its particular geometric structure makes La Plata well-designed, more efficient and less vulnerable.

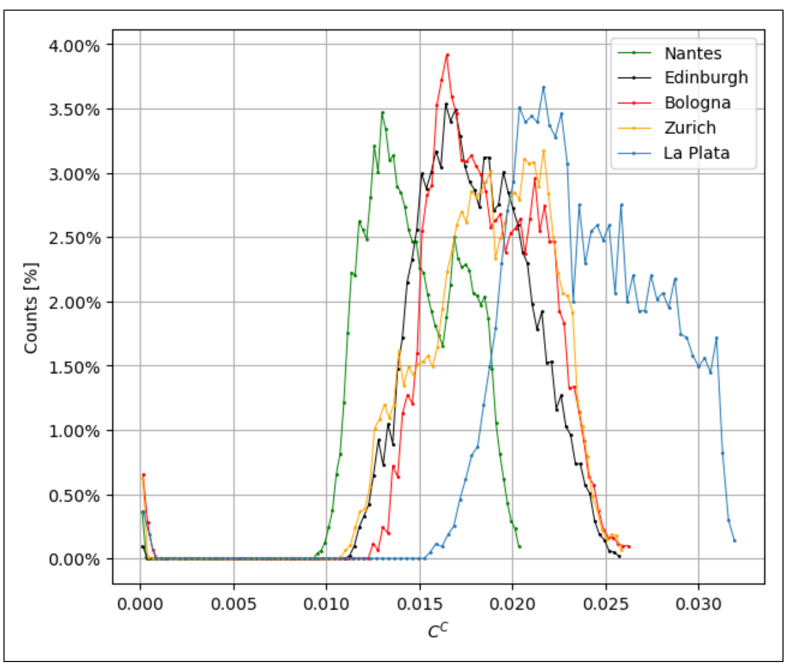


Figure 11: *Distribution of closeness centrality C^c for the traffic networks of Nantes, Edinburgh, Bologna, Zurich, and La Plata*

3.2.3 Vulnerability analysis

Table 3 presents the vulnerability factors computed as described in eq. 10. The following streets were removed from the analysis:

- *Bologna*: Via dell'Indipendenza, Via Francesco Rizzoli, Via Ugo Bassi
- *Nantes*: Rue du Calvaire, Cours des Cinquante Otages, Cours Olivier de Clisson
- *Edinburgh*: Lothian Road, Cockburn Street, North Bridge, St Mary's Street
- *Zurich*: Langstrasse
- *La Plata*: Diagonal 74

We took ZTL streets name of Nantes, Edinburgh and Zurich from references [14], [15] and [16].
The results show that Bologna is the most vulnerable among the cities analyzed. Despite removing a comparable number of nodes from Bologna's urban network as from Zurich's, Bologna's vulnerability factor is more than double that of the other cities.
This could be due to the fact that the removed streets in Bologna are the two main city center axes. These are touristic and commercial streets, closed on weekends or holidays, during which only pedestrians are allowed to walk along these streets.
In contrast, Nantes is the least vulnerable city, also considering that the number of removed nodes was double compared to Zurich.

Vulnerability Factors			
City	**Vulnerability**	**# Nodes removed**	**Vulnerability per node removed**
Bologna	0.207	19	0.011
Nantes	0.075	35	0.002
Edinburgh	0.091	23	0.003
Zurich	0.045	18	0.002
La Plata	0.114	42	0.002

Table 3: *Vulnerability factors and number of nodes removed from every graph. The vulnerability factors are computed over a* $3.8km^2$ *area.*

3.3 Simulation results

We simulated 3000 cars and let them drive through a $50km^2$ Bologna urban network for a total of 48 'real life' hours, both for *Città50* and *Zona30* speeds limits.
The resulting maps from simulation are shown in Figures 12, 13, 14 and 15. They are a comparison between images obtained from the simulation and real data. The values are normalized in order to have a fair comparison.

Figure 12 and 13 show traffic simulation result compared to real traffic data. Passing from *Città50* to *Zona30* we notice a significant decrease in traffic flow through the city center in favour of those few streets who have $50\frac{km}{h}$ limit.
This is particularly evident with the *Viali*, streets surrounding the city center that play a crucial role in Edge Betweenness Centrality, as it's seen from Figure 7.

Figures 14 and 15 instead compare the simulated accidents position with the real ones. Such comparison is missing in the *Zona30* scenario since 2024 accidents data have not yet been collected. Accidents position basically follow the traffic flow distribution in both cases.
Figure 16 shows travel times histograms, the distributions of time taken to reach the target, while Table 4 summarizes and compares the statistics from the two speed limit systems.

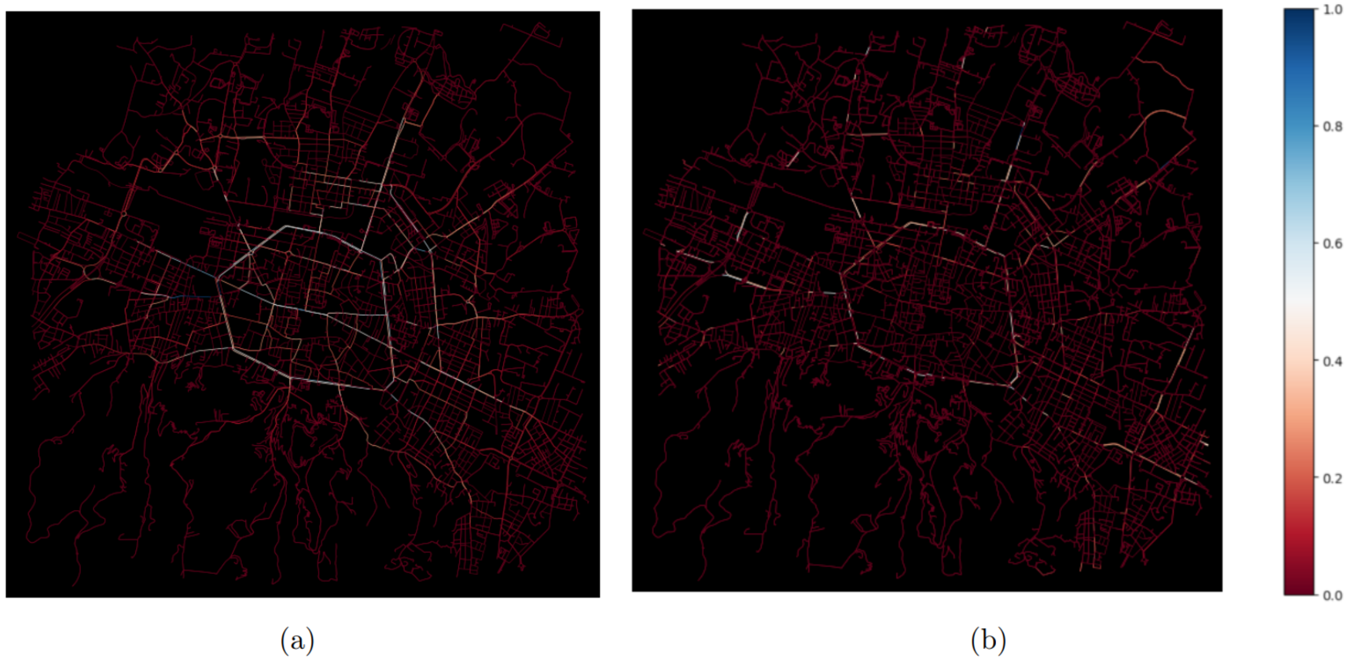


Figure 12: *Città50* traffic flow maps: ***a)*** *Simulated,* ***b)*** *Real data*

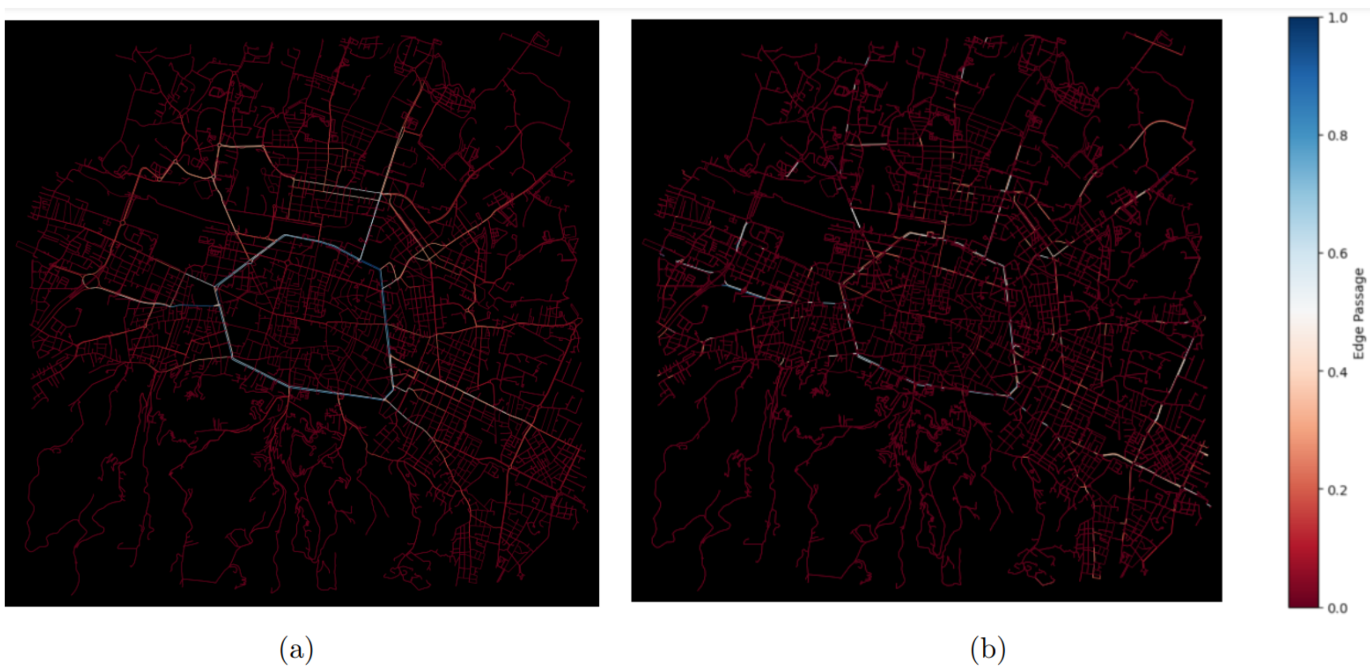
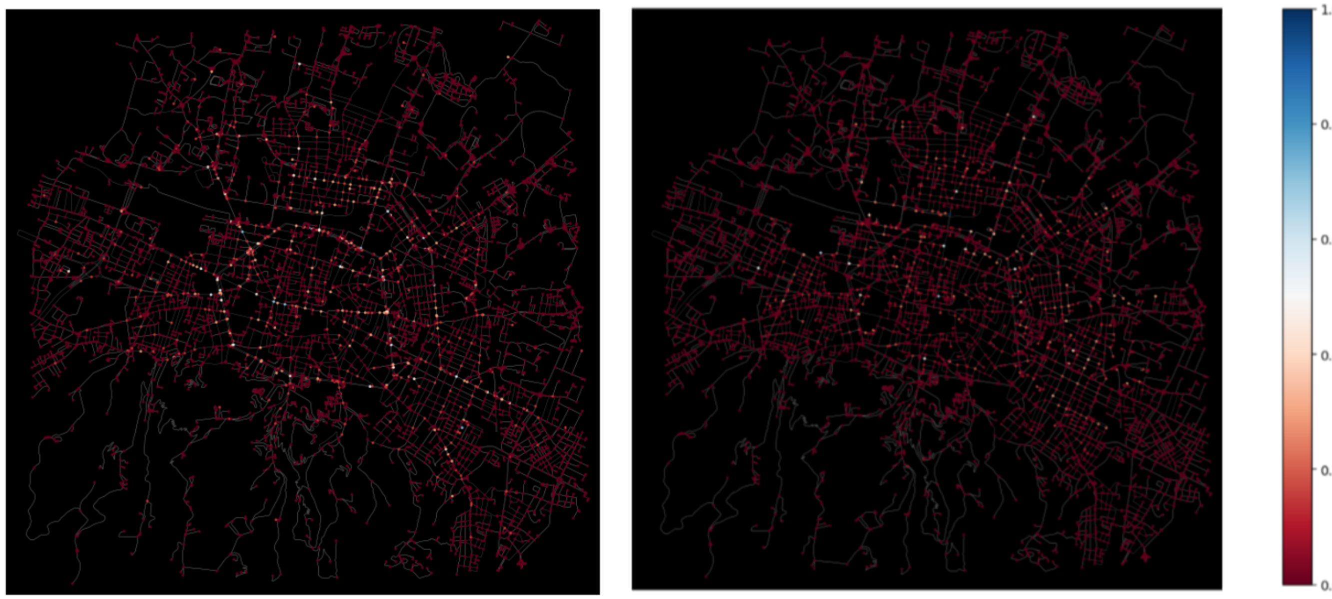


Figure 13: *Zona30* traffic flow maps: ***a)*** *Simulated,* ***b)*** *Real data*



(a) (b)

Figure 14: *Città50 accidents maps:* ***a)*** *Simulated,* ***b)*** *Real data*

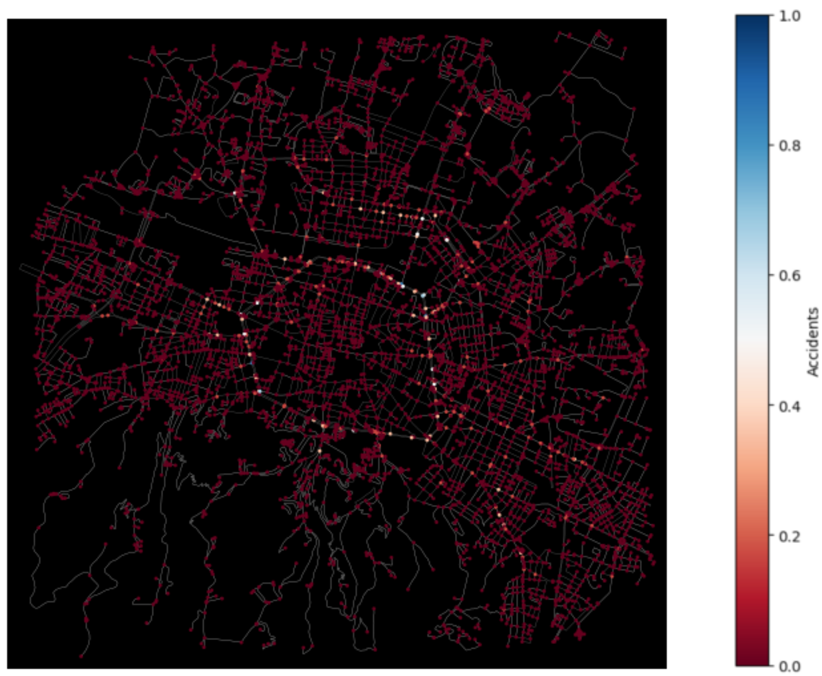
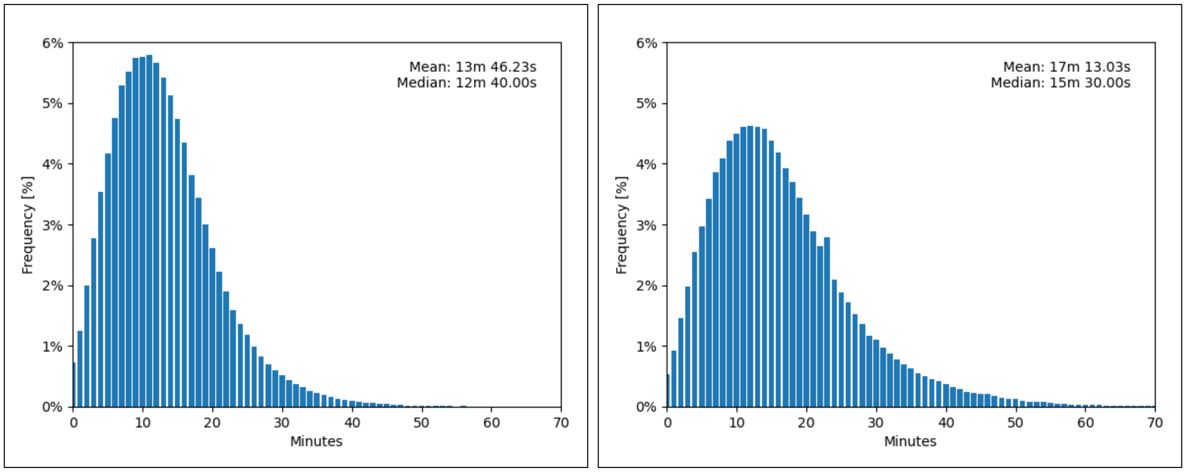


Figure 15: *Zona30 simulated accidents maps. Real data are missing from the dataset.*



(a) (b)

Figure 16: *Travel times histogram comparison:* ***a)*** *Città50,* ***b)*** *Zona30*

	Città50	***Zona30***
Mean speed	25.97 $\frac{km}{h}$	17.60 $\frac{km}{h}$
Mean travel time	13 m 46 s	17 m 13 s
Median travel time	12 m 40 s	15 m 30 s
Mean acceleration	3.93 $\frac{km}{h \cdot s}$	2.74 $\frac{km}{h \cdot s}$
# Accidents	962	400
% Accuracy traffic simulation	87.69 %	89.84 %
% Accuracy accidents position	86.45 %	NO DATA

Table 4: *Statistics comparison between Città50 and Zona30 after 48 'real life' hours simulated.*

Number of accidents per year	
Year	**# Accidents**
2010	1170
2011	1293
2012	1040
2013	998
2014	972
2015	975
2016	1023
2017	1009
2018	1037
2019	1017
2020	715
2021	998
2022	1111

Table 5: *Number of accidents from real data per year. It refers to an area of* $28km^2$.

We notice how the introduction of *Zona30* speed limits in our simulation lowers the mean speed by $\sim 32\%$, and as consequence the mean travel time increases by $\sim 25\%$.

Since traffic lights are neglected in our simulation, travel times must be readed as lower limits. Also the mean acceleration undergoes a decrease of $\sim 30\%$.
As expected, the number of accidents is less than the half, decreasing by $\sim 58\%$, since the accident probability is parametrized as a non-linear distribution depending only on the relative speeds between two cars (Figure 6).
Accuracy values show a good match between simulated and real traffic flow, reaching a minimun accuracy of 87.69%, while the only accuracy available for accidents position is slightly less but still satisfying. For an explaination on how we computed those accuracies see the Appendix (section 4).

Regarding the accidents number, we need to specify that we tuned our simulation to generate a high number of accidents per day simulated, to facilitate comparison with real accidents data, as shown in Table 5. This was necessary due to the significant computational time required to simulate an entire year. If a more realistic simulation is desired, the internal accident dynamics and its distribution, given in Figure 6, would need to be recalibrated.

4 Conclusions and Outlook

In this report we used the Complex Network framework to analyze and compare five urban road networks, and to build a traffic simulation to predict the effects of *Zona30* in Bologna.

The connectivity analysis, shown in Table 1, describes Bologna as less cyclical and complex compared to other cities, even if good level of connectivity is achieved anyway. The centrality analysis show how Bologna urban network relies on few crucial edges, like other self-made cities, but unlike them it is the most vulnerable one, as it's reported in section 3.2.3.

Our simulation turned out to predict correctly the effects of introducing *Zona30* in Bologna, as it can be seen in Table 4. From an obvious decrease in mean speed follows an increase in mean travel time, and the main benefits are reproduced correctly, such as the sharp accidents number decrease and the decrease in mean acceleration, result of a more stable driving. There is a good agreement between our simulation and real traffic and accident data, as it can be seen from accuracy values. A more detailed analysis on *Zona30* accidents prediction can be done after the collection of new accident data, starting from January 2024.
To improve the realism of the simulation some steps can be followed. Introducing traffic lights and a variable number of cars through time can make travel times more realistic. Using a different method to assign initial and final node, instead of Closeness Centrality distribution, can strongly improve the realism of traffic flow through city center, that in the *Zona30* scenario is almost absent. A distribution of final nodes based on city points of interest (offices, schools, markets, ...) can, in principle, solve this problem.

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Appendix

To compute the traffic simulation accuracies, reported in Table 4, we compared two vectors, $\vec{sim}$ and $\vec{data}$, both with length = *Number of edges*.
$\vec{sim}$ is the resulting array of the simulation. Its i_{th} entry is the number of times a car drove through the i_{th} edge. $\vec{data}$ is analogous but with real data.
The values of both arrays is normalized between 0 and 1 in order to compare them.

To quantify how far the simulation is from real data we took the difference of those two arrays and compared it with a difference between an array of ones and an array of zeros, which represents the "worst" case.
The accuracy is therefore computed as follows:

$$Accuracy = 1 - \frac{\|\vec{sim} - \vec{data}\|}{\|\vec{1} - \vec{0}\|} \tag{12}$$

Where $\vec{1}$ and $\vec{0}$ are two arrays filled up with ones and zeros. Their length is equal to the number of non-zero element in $\vec{sim} - \vec{data}$.
The simulated accident accuracy is computed similarly working on nodes instead of edges.