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Chair of Data Visualization

Towards AI-Optimized Traffic: Agent-Based Modelling for Urban Mobility Solutions

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Abstract

Urban mobility is increasingly challenged by congestion, environmental impacts and inefficiencies inherent in traditional transport management systems and aging infrastructures. This study employs an agent-based modeling approach using NetLogo to simulate and analyze urban traffic dynamics in Geneva and Rome, two cities characterized by distinct urban structures, transportation policies, and cultural attitudes toward mobility.

The research aims to identify traffic patterns under varying simulated scenarios, compare urban mobility between the two cities, evaluate the efficiency of different transportation methods, and analyze opportunities for improvement in urban mobility systems. The simulation integrates real-world data, including OpenStreetMap networks and TomTom congestion data, to enhance accuracy and reliability. In the model, agents behave as fully rational individuals, always selecting the shortest route through the A* pathfinding algorithm.

Results from the simulations highlight substantial differences in transportation efficiency. In ideal traffic conditions, private vehicles are shown to be the most efficient mode of transportation. Under realistic, congested scenarios, alternative modes such as cycling and public transport significantly outperform cars, particularly in Geneva, due to its robust cycling infrastructure and compact urban design. Conversely, Rome's extensive reliance on cars, coupled with limited infrastructure for alternative modes, exacerbates congestion, emphasizing the necessity for systemic infrastructure enhancements and cultural shifts towards sustainable mobility.

This study's innovative contribution lies in demonstrating the capability of ABM to produce actionable insights with limited computational resources, effectively guiding urban planning and policy decisions. The research highlights the utter contrasts between Geneva's proactive infrastructure developments and Rome's entrenched car dependence, underscoring the importance of context-specific, sustainable transport strategies tailored to each city's unique characteristics.

GitHub Repository:
https://github.com/4lucolo20/Rome-Geneva-Traffic-Simulation

1. Introduction

The way cities evolve has always reflected how people move within them. Since the earliest settlements, urban spaces have taken shape around the need to enable mobility, whether for trade, daily work, or social interaction. The Industrial Revolution marked a turning point, driving rapid urban expansion and putting pressure on existing transport systems. Later, the rise of private car ownership in the twentieth century radically transformed urban design, leading to the spread of highways and the emergence of car-centric suburbs. Today, as cities grow larger and more complex, the challenge of rethinking how humans plan and manage mobility systems has become more pressing than ever.

Modern urban mobility is characterized by increasing congestion, environmental concerns, and the need for more sustainable transport solutions. Rapid urbanization has led to a surge in private vehicle ownership, placing immense pressure on existing road networks[1]. Traffic congestion not only results in longer travel times but also contributes to higher fuel consumption and emissions, as well as negatively impacting economic productivity, as delays and unreliable mobility options hinder the smooth functioning of cities[2]. Beyond the technical opportunity cost, time lost in traffic deprives individuals of moments that could be spent on leisure or meaningful personal activities, ultimately reducing overall quality of life. A 2024 study reveals that drivers in four major cities - Istanbul, Turkey; Chicago and New York, USA; and London, UK - spend an average of over 100 hours per year stuck in traffic. Rome ranks as the first Italian city in this unfavorable list, placing 17th, with residents losing approximately 71 hours annually to gridlock[3]. An average daily schedule of 7 hours of sleep and 8 hours of work means that around 2% of an individual's yearly ‘free’ time is lost to traffic, taking away precious hours from leisure and meaningful personal activities. While this percentage may not seem alarming at first glance, over an average lifetime, it amounts to a staggering 5.893 hours, equivalent to nearly eight whole months, spent idling in traffic. Paradoxically, the very lifespan for this calculation is itself reduced by prolonged exposure to air pollution from motionless vehicle emissions, creating a dual burden of lost time and compromised health.

Traditional approaches to traffic management, such as fixed traffic light cycles, rigid public transport timetables, and static road layouts, often fall short when faced with the dynamic nature of modern urban life. These systems are typically unable to adjust to real-time changes in traffic conditions, resulting in congestion, uneven use of infrastructure and suboptimal distribution of transport capacity. At the same time, connecting different transport options, like buses, trains, cycling routes and ride-sharing platforms, remains a complex task in many urban contexts. In the absence of smooth integration, commuters often encounter fragmented journeys, which discourages multimodal travel and reinforces the tendency to rely on private

[1] Hemilä, J., Kettunen, O., & Ollus, M. (2009). Management View on Intelligent Intermodal Transport. 16th ITS World Congress and Exhibition on Intelligent Transport Systems and ServicesITS AmericaERTICOITS Japan. https://trid.trb.org/view.aspx?id=911444

[2] Abbas, Q., Alyas, T., Alyas, T., Alghamdi, T., Alsaawy, Y., & Alzahrani, A. (2023). Revolutionizing Urban Mobility: IoT-Enhanced Autonomous Parking Solutions with Transfer Learning for Smart Cities. Sensors, 23(21), 8753.

[3] INRIX (7. January, 2025). Congestions most conspicuous conurbations worldwide in 2024 (by time loss per year). InStatista Accessed on 16. March 2025, from https://de.statista.com/statistik/daten/studie/970465/umfrage/stauauffaelligste-ballungsraeume-weltweit/

vehicles. This, in turn, feeds back into the very congestion these systems are meant to alleviate.

2. Foundations of the Research

Data is an incredibly powerful tool, pervasive in every aspect of our daily lives, often without us even realizing it. Over the past few decades, data analytics has expanded beyond technological experts to become a common part of everyday life. In the context of this research, data-driven tools have gained widespread use, even among parts of the population who may not consider themselves tech-savvy. Navigation systems like Google Maps or Waze have become indispensable for millions of commuters, as well as ride-sharing apps and public transportation platforms facilitate convenient and flexible mobility. This shift in the everyday employment of data by the general population has opened new avenues for optimizing urban mobility, especially considering the real-time applications they offer.

2.1 Motivation and Context

This project will examine two cities with fundamentally different transportation systems and commuting trends, not for direct comparison but to explore how distinct solutions can be tailored to diverse urban environments. These cities are also personally significant to me: Rome, where I spent some of the most formative and eventful years of my life, and Geneva, where I began my professional career abroad.

Rome, often referred to as an open-air museum, makes walking particularly enjoyable, with its culture-rich and vibrant atmosphere enhancing the experience. However, as an intrinsic consequence of its millennial history, the city's urban landscape, characterized by narrow streets, steep turns, and limited space, was not designed with large-scale public transport or modern infrastructure in mind, forcing reliance on inefficient, and in most cases unsustainable, means of transport.

On the other hand, the characteristics of Geneva, with its surface area being almost a hundredth of Rome’s one and hosting one-tenth of the population, make it far more manageable in terms of traffic and urban planning. The city’s more modern infrastructure and relatively smaller size allow for greater integration of efficient public transport and progressive sustainable mobility options, such as an extensive tram network and a focus on promoting cycling and pedestrian-friendly spaces.

While both cities present unique challenges and opportunities, this project aims to explore how different transportation solutions can be applied to meet the specific needs of each city’s infrastructure and population density and habits. In this regard, the project becomes particularly relevant: by examining traffic trends, urban development, and the centrality of key junctions, the overarching aim is to develop tailored transportation strategies that integrate various modes of transport, involving public transit, pedestrian and active transportation, and private vehicles.

In the past, urban transportation planning relied heavily on the Four-Step Travel Demand Model, a top-down, aggregate method dividing planning into trip generation, distribution, modal split, and assignment. While useful for long-range planning, such traditional models often struggle to capture individual behavioral adaptations and real-time network feedback[4]. Over the last two decades, and especially in the last five years, agent-based modeling has emerged as a bottom-up alternative that can simulate each traveler or vehicle as an autonomous "agent" making decisions, thereby reproducing emergent traffic patterns from the ground up. The distinction between these new approaches and the more aggregate, static conceptions and representations that they seek to complement, if not replace, is that they facilitate the exploration of system processes at the level of their constituent elements, enabling unprecedented degrees of variability and granularity across their components.

The increased specialization and diversity afforded by agent-based approaches make them particularly well-suited for research projects focused on urban mobility and transport efficiency. In light of these strengths, this thesis seeks to address the following research questions:

1. What is the most efficient mode of transportation under ideal conditions, where vehicles travel at the speed limit and congestion is absent, and can this be further optimized?

2. In a day-trip scenario, which mode offers the best travel solution, considering slower movement and planned stops?

3. Under congested rush hour conditions, would individuals be better off if they behaved rationally, switching modes to avoid traffic bottlenecks as the model allows?

At the heart of agent-based modeling lies the concept of the *agent*, a discrete, autonomous entity endowed with specific behavioral rules, preferences, and decision-making capabilities. In the context of urban mobility, agents typically represent individual commuters, drivers, pedestrians or vehicles, each with their own travel goals, modes of transportation and adaptive responses to their environment; characteristics that make them particularly suitable for scenario simulations. Diversity in their applications makes agent characteristics and definition difficult to identify in a consistent and concise manner, but it is possible to identify several features common to most agents:

- **Autonomy:** agents are autonomous units, capable of processing and exchanging information with other agents, making them independent decision-makers.

- **Heterogeneity:** agents represent autonomous individuals, each with distinctive demographic or behavioral identifiers; this allows deep granularity and personalization. Groups of agents sharing common features can exist as

[4] Hofer, C., Jäger, G. & Füllsack, M. Including traffic jam avoidance in an agent-based network model. Comput Soc Netw 5, 5 (2018). https://doi.org/10.1186/s40649-018-0053-y

the result of the amalgamations of similar autonomous individuals, mimicking task-driven top-down approaches typical of traditional modeling methods, while still retaining the complexity and singularity of each individual agent.

- **Active:** autonomy and heterogeneity enable agents to exert independent influence in a simulation. Depending on their scope, agents can have different degrees of activity:

  - **Pro-active/goal-directed**: agents might be assigned goals to achieve (not necessarily objectives to maximize) with respect to their behaviors.

  - **Reactive/Perceptive:** agents can be designed to have an awareness or sense of their surroundings, allowing them to elaborate spatial data.

  - **Bounded/Full Rationality:** Rational-choice models generally assume that agents are perfectly rational optimizers with unlimited access to information, foresight, and infinite analytical ability. However, agents can be configured with ‘bounded’ rationality (through their heterogeneity). This allows agents to make inductive, discrete, and adaptive choices that move them towards achieving goals[5].

  - **Interactive/Communicative:** agents have the ability to communicate extensively in the form of data and information exchange.

  - **Mobility:** agents can ‘roam’ the space within a model, incorporating also a spatial or physical dimension.

  - **Adaptation/Learning:** agents can be designed to alter their state depending on previous states, permitting them to adapt with a form of memory or learning. Models where agents adapt at the individual micro-level or at group macro-level produce Complex Adaptive Systems (CAS), the most coarse-grained form of simulation[6].

Building on the foundational elements of ABM and the defined characteristics of agents, the choice of Rome and Geneva as case studies represents an ideal setting to apply this modeling approach. Their markedly different urban morphologies, population densities, transport infrastructures, and modal preferences create a natural testbed for leveraging heterogeneity in simulating and managing complex mobility systems.

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[5] Parker, D.C., et al. (2003) Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. Annals of the Association of American Geographers, 93, 314-337. https://doi.org/10.1111/1467-8306.9302004

[6] Holland, J.H. Studying Complex Adaptive Systems. Jrl Syst Sci & Complex 19, 1–8 (2006). https://doi.org/10.1007/s11424-006-0001-z

	Rome	Geneva
Surface Area (km^2)	1.285	15,92
Population	2.746.984	201.741
# Traffic Lights	1457[7]	~280
Motorization Rate (per 100 inhabitants)	61%[8]	37%[9]
Bike Lanes Aggregate Length (km)	321[10]	64[11]
Bike to Extension Rate	25%	402%

Table 1. Rome and Geneva comparison of morphological and urban layout statistics.

Rome's sprawling layout, informal driving culture, and reliance on private vehicles contrast sharply with Geneva's compact geography, structured multimodal transport system, and coordinated cross-border commuting flows. In such a dual setting, the ability to assign distinct behavioral profiles to agents becomes not just advantageous, but essential, accommodating the distinct ways in which commuters in each city respond to congestion, route availability, and travel alternatives. A single, homogeneous model would risk overgeneralization and lose explanatory power in these contrasting environments. The heterogeneity and autonomy of agents become particularly valuable for modeling behaviors reflecting frequent illegal parking, non-compliance with traffic norms, and low modal shift elasticity, in Rome, while Geneva's agents can be equipped with higher propensities for multimodal transport use, sensitivity to schedule adherence, and reliance on well-integrated tram or train lines. This level of specificity supports accurate scenario testing and context-sensitive behavior, possibilities that traditional top-down approaches would exclude.

	Rome	Geneva
# Nodes	43.657	1.076
# Edges	90.434	3.376
Diameter (in # edges)	234	69
Diameter (in meters)	35.976	6.930

Table 2. Rome and Geneva comparison of graphs descriptive statics.

[7]https://romamobilita.it/it/tecnologie/impianti-semaforici#:~:text=Tutti%20gli%20impianti%20semaforici%20di,UTC)%20e%20577%20non%20centralizzati.
[8] Euromobility. (December 2, 2019). Number of cars per 100 inhabitants in selected Italian cities in 2018. In Statista. Retrieved May 23, 2025 from https://statista.com/statistics/1077673/motorization-rate-italy-by-city/
[9] FSO, FEDRO – New Registrations of Road Vehicles (IVS) https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport/transport-infrastructure-vehicles/vehicles/road-new-registrations.html
[10] Roma Mobilità - https://romamobilita.it/it/muoversiaroma/ciclabilita
[11] Carte vélo Ville de Genève - https://www.ge.ch/document/carte-velo

Considering both cities at system-wide level, this approach also provide significant insights into the complex feedback systems that challenge equilibrium-based models[12]. In Rome, even minor disruptions can cause systemic gridlock, while in Geneva, small modal shifts can produce meaningful changes in congestion levels due to the city's spatial constraints. ABM, grounded in systems theory, is uniquely equipped to simulate these nonlinear dynamics. It captures how local interactions among agents, such as drivers re-routing simultaneously to avoid traffic or pedestrians switching to cycling, can yield emergent patterns like congestion cascades or temporary equilibria.

Figure 1. Networks Diameter of (a) Geneva and (b) Rome.

Figure 1 pictures the importance of tailoring models specific to the context. The Geneva network is composed of 3.376 edges for 1.076 nodes, while Rome graph consists of 90.434 edges serving 43.657 nodes. Nodes (or vertices) are individual entities from which graphs are constructed, connected and communicating with each other through edges. In the model, nodes represent intersections, junctions and any point of interest relevant when navigating a street network, such as where a road changes attributes like direction or speed limit. The edges represent the actual roads and streets connecting the nodes. When applied to urban street networks, the diameter offers insight into the compactness and connectivity of a city's layout. A smaller diameter typically reflects dense, well-connected urban fabric, and more efficient traffic routing. Larger diameters are often associated with urban sprawl, a condition in which cities expand in a fragmented and unplanned manner, leading to lower density and poor network connectivity. With this mind, the networks diameters confirm the visual cues from the cities' layouts: Rome's diameter in edges is 3,4 times longer than the Geneva one, 5,2 times longer if measure in meters.

[12] K. B. Sibale and K. G. . Munthali, "Analysing Road Traffic Situation in Lilongwe: An Agent Based Modelling (ABM) Approach", Adv. J. Grad. Res., vol. 10, no. 1, pp. 3–15, Mar. 2021.

2.2 Literature Review

The increasing complexity of urban mobility has led to significant challenges in traffic management, congestion mitigation, and transportation planning. Traditional approaches to traffic modeling, such as macroscopic and mesoscopic models, rely on aggregate-level analysis and often fail to capture the heterogeneity of individual behavior. Macroscopic models generally allow the representation of large road networks with an acceptable computational load. This computational advantage is counterbalanced by the lack of precision in capturing specific traffic phenomena related to the behavior of individual drivers. On the opposite side, microscopic models describe the dynamic behavior of every single vehicle in the traffic stream, trying to capture the interactions among vehicles and between vehicles and the road infrastructure. These models can be very detailed and accurate in representing specific traffic features but, of course, are very demanding from a computational point of view, making them mostly used to analyze specific reduced areas or for trial tests[13].

In contrast, Agent-Based Modeling (ABM) offers a different way of simulating traffic systems by focusing on the behavior of individual components. Rather than relying on aggregated data and fixed equations, ABM builds from the bottom up, allowing complex system-wide patterns to emerge from the actions and interactions of individual agents. In traffic simulations, these agents can take the form of drivers, vehicles, pedestrians, or even elements of the infrastructure itself, each defined by specific attributes such as speed, route choice, and reaction time. What makes this approach particularly effective is its ability to reflect the heterogeneity of real-world behavior—agents differ from one another, react to their surroundings, and in some cases adapt over time. This level of detail makes it possible to reproduce dynamics like traffic jams or emergency evacuations, which are often the result of local interactions and would be difficult to anticipate with more traditional modeling methods[14].

The development of Agent-Based Modeling has mirrored the increasing availability of data and the broader interest in simulating complex systems at a finer level of detail. Early conceptual models, like Schelling's segregation simulation from 1971, showed how simple rules, such as agents relocating when fewer than 40% of their neighbors shared a specific trait, could lead to intricate spatial patterns[15]. This foundational work demonstrated the potential of ABM to connect individual choices to large-scale outcomes, as well as its capacity for capturing personalized dynamics. By the mid-1990s, Epstein and Axtell's SugarScape project took this further, modeling artificial societies where agents competed for resources like "sugar," and in doing so revealed emergent behaviors including inequality, trade networks, and the spread of cultural norms[16]. These models underscored ABM's ability to simulate processes, such as adaptation and competition, rather than static states.

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[13] Ferrara, A., Sacone, S., Siri, S. (2018). Microscopic and Mesoscopic Traffic Models. In: Freeway Traffic Modelling and Control. Advances in Industrial Control. Springer, Cham. https://doi.org/10.1007/978-3-319-75961-6_5

[14] Crooks, Andrew. (2015). Agent-based Models and Geographical Information Systems.

[15] Schelling, T.C. (1971) Dynamic Models of Segregation. Journal of Mathematical Sociology, 1, 143-186. http://dx.doi.org/10.1080/0022250X.1971.9989794

[16] Duffy, John. *Southern Economic Journal*, vol. 64, no. 3, 1998, pp. 791–94. *JSTOR*, https://doi.org/10.2307/1060800. Accessed 31 Mar. 2025.

In the field of transportation, ABM's value became increasingly apparent through models that reproduced traffic flow dynamics. Wilensky's 1997 simulation, for instance, used simple rules such as slowing down when another car is ahead, yet still managed to replicate stop-and-go traffic waves, often referred to as "rubbernecking" effects, without requiring any physical obstruction[17]. Later, ABMs incorporated greater realism, such as integrating GIS-based road networks or modeling multimodal transport choices (e.g., car vs. bus)[18]. The framework's flexibility also enabled applications beyond academia: Southwest Airlines optimized cargo logistics, while urban planners used ABM to test evacuation protocols or congestion pricing.

More recent advancements in ABM for urban traffic optimization have proven particularly effective for modeling complex mobility patterns in cities with high spatial and behavioral heterogeneity. These high-resolution simulations often draw on detailed data and require significant computational power. Projects like MATSim, which have been applied in cities such as Zurich and Berlin, simulate individual travel patterns using activity chains, route preferences, and mode switching, all running on high-performance computing clusters capable of processing millions of agents[19]. Similarly, POLARIS, developed by the U.S. Department of Energy, employs ABM to optimize traffic signals and evacuation routes by modeling adaptive driver behavior, necessitating both supercomputing infrastructure and proprietary software[20]. In Rome, recent work has explored congestion pricing in terms of environmental pollution using ABM run through large-scale, GPU-accelerated simulations[21], while Geneva has seen applications in exploring human decision-making in multimodal traffic integrations via computationally intensive discrete-choice models[22].

These examples illustrate the strength of ABM in testing policy scenarios at a granular level, such as low-emission zones or dynamic tolling systems. However, they also highlight a clear limitation: the models' dependence on heavy infrastructure and proprietary tools makes them less accessible to researchers or decision-makers without significant computational resources. Full-scale MATSim implementations, for instance, often require terabytes of RAM and can take several days to run, while POLARIS depends on licensed solvers like Gurobi. These constraints make it difficult for smaller cities or universities to take full advantage of ABM's potential. This thesis addresses that challenge by proposing a streamlined approach that maintains analytical depth while emphasizing adaptability and computational efficiency, making it more suitable for resource-constrained settings.

[17] Wilensky, Uri & Resnick, Mitchel. (1999). Thinking in Levels: A Dynamic Systems Approach to Making Sense of the World. Journal of Science Education and Technology. 8. 3-19. 10.1023/A:1009421303064.

[18] Benenson, Itzhak & Torrens, Paul. (2004). Geosimulation: Automata-Based Modeling of Urban Phenomena. 10.1002/0470020997.

[19] Grunicke, Conny & Schlueter, Jan & Jokinen, Jani-Pekka. (2020). Implementation of a cost-benefit analysis of Demand-Responsive Transport with a Multi-Agent Transport Simulation. 10.48550/arXiv.2011.12869.

[20] Auld, Joshua & Hope, Michael & Ley, Hubert & Sokolov, Vadim & Xu, Bo & Zhang, Kuilin. (2015). POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. Transportation Research Part C: Emerging Technologies. 64. 10.1016/j.trc.2015.07.017.

[21] Cipriani, Ernesto & Mannini, Livia & Montemarani, Barbara & Nigro, Marialisa & Petrelli, Marco. (2018). Congestion Pricing Policies: Design and Assessment for the city of Rome, Italy. Transport Policy. 80. 10.1016/j.tranpol.2018.10.004.

[22] Bierlaire et al. (2020). Multimodal Integration in Geneva: A Behavioral ABM Approach. Transport Policy.

Three key distinctions emerge:

- **Resource-Aware Modeling:** Unlike MATSim, which typically requires access to high-performance computing infrastructure, or POLARIS, which depends on licensed optimization tools, this framework produces policy-relevant insights using open-source environments like NetLogo and Mesa on standard hardware. Rather than attempting to model entire metropolitan areas in full detail, it concentrates computational effort on high-impact subsystems, such as Rome's Limited Traffic Zones (ZTL) or Geneva's cross-border commuting corridors. This selective focus helps preserve analytical depth where it matters most while avoiding unnecessary complexity in less critical areas. Efficiency is further improved by using streamlined agent behaviors, such as bounded-rationality mode choices, calibrated against local travel data, which strike a balance between realism and computational simplicity.

- **Empirical Anchoring with Pragmatic Data:** Where large-scale models often rely on abstract assumptions, like system-wide utility functions or generalized origin-destination matrices, this framework roots agent behavior in concrete, context-specific observations. In Rome, for instance, behavioral assumptions reflect a strong preference for private vehicle use and a high tolerance for informal parking, patterns captured through traffic count data and violation records. In Geneva, cross-border commuters' reliance on regional public transport has been incorporated without the need for computationally demanding discrete-choice modeling. This form of targeted calibration enables a credible representation of agent behavior, even when granular or real-time datasets are unavailable—a frequent constraint in mid-sized cities with limited digital infrastructure.

- **Modular Policy Testing:** Thanks to its modular design, the model can support rapid scenario testing without requiring a complete reconfiguration of the system. This flexibility allows interventions to be introduced, adjusted, and re-tested iteratively, offering a level of responsiveness rarely possible in large-scale agent-based systems, where technical complexity often obscures cause-and-effect relationships. For policymakers, this means being able to explore a wide range of targeted policy options—from traffic restrictions to modal incentives—without committing to a full system overhaul at each stage.

These differences enable the exploration of new perspectives on urban governance: by demonstrating that actionable insights need not require industrial-scale computation, this work expands ABM's accessibility to resource-constrained contexts. The approach is particularly salient for large and mid-sized European cities like Rome and Geneva, where traffic dynamics are often localized (e.g., historic-center congestion) but poorly served by models designed for megacities.

Crucially, the framework does not dismiss high-resolution ABMs but instead offers a complementary pathway, one that acknowledges the 80/20 Pareto rule of urban policy analysis: often, 80% of actionable insights derive from 20% of a system's complexity[23].

2.3 Data Sources

The reliability of any simulation hinges on the quality and scope of its underlying data. In this study, multiple data sources were used to construct, enrich, and calibrate the simulation environment for Rome and Geneva. These datasets range from open geospatial data to real-time traffic records and public transport schedules, ensuring that agent behavior is grounded in contextual, empirical input. This section outlines the data sources, formats, and preprocessing steps that underpinned the construction of the dual-layer transportation networks and the behavioral logic of the agents.

- **Geographic Network Data: OpenStreetMap[24]:** the foundational data for constructing both the driving and walking networks were retrieved via the OpenStreetMap (OSM) Editing API, accessed through the `osmnx` Python library. For each city, the "drive" and "walk" network were downloaded, yielding nodes and edges representing street intersections and road segments, respectively. Each edge record includes road attributes that revealed crucial in the final analysis, discussed in Chapter 2.4. All geospatial data were projected using EPSG:4326, as required by NetLogo's GIS extension. Distance normalization and travel speed conversions were performed in Python, and extensive visual checks were conducted using `geopandas` and `contextily` for `basemap` validation. Walking and driving paths were integrated from separate shapefiles, filtered to avoid duplication of common edges and reduce dimensionality. To reconcile coordinate distortions between projection systems, manual stretching and adjustment of the NetLogo basemap were performed using the `resize-world` command.

- **Traffic Data: TomTom Developer API[25]:** to integrate real-world congestion patterns, data was sourced from the TomTom Developer API, which provided travel time and speed metrics for each road segment in August 2024. Despite seasonal limitations, this dataset offered valuable insight into structural bottlenecks and enabled relative comparisons between free-flow and congested conditions. These values were matched to the corresponding edges in the network and used to adjust agent speed profiles during congestion simulations.

- **Public Transport Data: TPG Open Data[26]:** the Transport Publics Genevois (TPG) open data portal provided detailed information on Geneva's tram and bus network. Two datasets were used:

[23] Koch, R. (1999). The 80/20 principle: the secret of achieving more with less (1st Currency paperback ed., p. X, 277). Currency; Doubleday.
[24] https://www.openstreetmap.org/#map=11/41.8586/12.6034
[25] https://developer.tomtom.com
[26] https://opendata.tpg.ch/explore/?sort=title

- Ridership per Day per Stop per Line, containing information on the route of each line;
- Stops, containing stop identifiers and coordinates.

The datasets were merged using stop IDs and spatially joined with the network nodes to flag public transport accessibility. This enabled pedestrian agents to include multimodal trips in their movement logic, simulating transitions between walking and public transport.

- **Public Transport Data: Roma Open Data[27]:** the Data Portal in Rome Municipality's website provides a Static GTFS dataset with geospatial information on public transport stops and lines.

2.4 Methodology

The collection and selection of resources to employ is a crucial step towards any data-related project, as it defines the further steps and shapes the process for getting to a solution. For the purpose of initially building the networks where agents will move, the OpenStreetMap[28] Editing API (henceforth, OSMx) was employed. It allows rapid fetching and saving of raw geodata, that serve as the main building blocks of the nodes and edges composing the road network. The resulting data from the OSMx extraction can be converted into two much more practical dataframes for cleaning and analysis, respectively containing nodes and edges. The nodes' one contains coordinates and references for localization, while the edges' one contains the following features:

Osmid	ID for the road segment. Unique identifier.
Oneway	Boolean. True if the road is one-way, False if it's two-way.
Lanes	The number of lanes in the road segment. Affects road capacity.
Ref	Road reference number (e.g., codes like "A1" for major roads).
Name	The name of the road (if available).
Highway	The road classification (e.g., "motorway", "primary", "residential").
Maxspeed	Speed limit in km/h.
Reversed	True if the direction is opposite to how it appears in OSM.
Length	Length of the road segment (in meters).
Bridge	Boolean. True if the road is a bridge.
Tunnel	Boolean. True if the road is a tunnel.

[27] https://dati.comune.roma.it/catalog/dataset/c_h501-d-9000/resource/266d82e1-ba53-4510-8a81-370880c4678f
[28] OpenStreetMap.org

Junction	Type of junction (e.g., "roundabout").
Access	Restrictions on road access (e.g., "private", "no", "yes").
Width	Road width (if available).

Table 3. Feature list of entries in the edges dataframe.

The features have varying degrees of usefulness and application for the purpose. `Length`, `oneway`, `lanes` and `highway` will be crucial for instructing agents on taking the shortest path and simulating realistic traffic conditions: agents will be aware of the length of edges (roads), whether they allow circulation on both directions, the number of lanes and what type of road it is. Having identifiers such as `names`, `junctions` and `access` will be especially useful for plotting roads' particularity from which to expect special behaviours from agents: the junction and access variables will influence the speed with which agents approach edges and whether they can enter them.

Once the raw geodata is extracted and cleaned, the next step is to construct the road network. This involves converting the two dataframes into shapefiles to retain their geographic features and merging them in a single file, that NetLogo will handle autonomously separating nodes and edges. Before enriching the code furtherly, visualizations were employed to ensure the correct processing of the geodata.

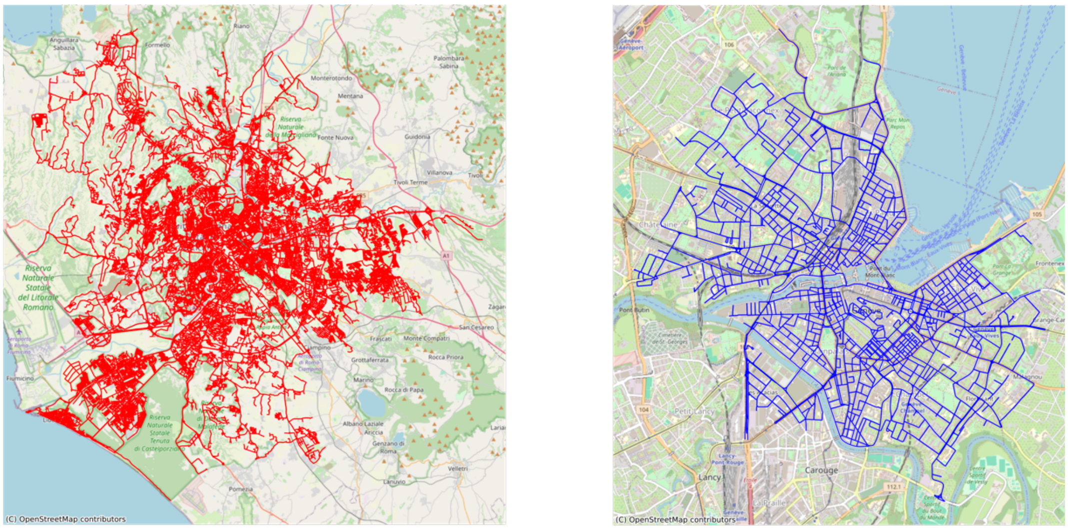


Figure 2. a) Rome Road Network. b) Geneva Road Network.

In order to augment the networks' information, speed limits and travel times were added to the edges graphs. Speed limits were defined from the `maxspeed` column, replacing the empty cells with 50 km/h for residential roads and 130 km/h for highways (for Italy). Ideal conditions travel times were computed on the basis of the edges' length and speed limit, using the latter as numerator and the former as denominator. They will be used as weights for the edges, representing a measure of cost, time or capacity associated with passing through it.

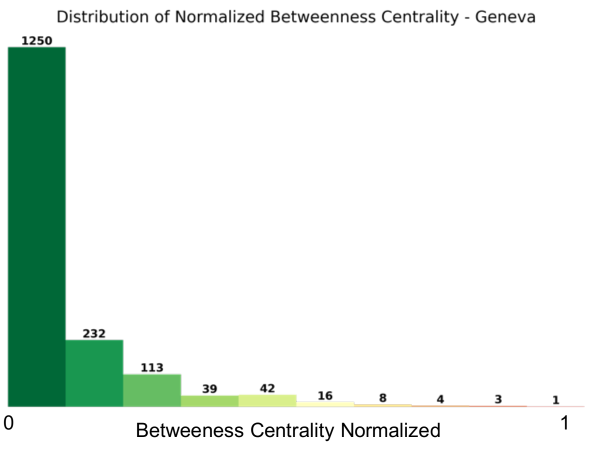
To identify congestion hotspots, the network's betweenness centrality is calculated using the NetworkX[29] library, a Python package for the creation, manipulation, and study of the structure and dynamics of complex networks (henceforth, Nx). Betweenness centrality quantifies the importance of a node (or edge) based on the number of shortest paths that pass through it. In a road network, nodes with high betweenness centrality are likely to experience more traffic, as they lie on the most efficient routes between many pairs of nodes. Mathematically, betweenness centrality for a node (v) is defined as:

$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Where:

- σ_{st} is the total number of shortest paths from node s to node t;
- $\sigma_{st}(v)$ is the number of those paths that pass through node v.

The previously created graphs were thus converted into directed graphs using the information contained in the `oneway` variable: roads might connect one way but not the other, which sensibly impacts the road layout and path choice, especially for cars. Edges labelled as one-way kept their original starting and end point, while for two-way lanes reversed starting and end-point were added. The Nx proprietary `betweeness_centrality` function was then used on the directed graph with the relative weights. This process is known to be computationally expensive, as it requires identifying all shortest paths in the network. In the case of Rome, the graph comprises 43.657 nodes and 90.334 edges, and the full computation took 4 hours. Geneva, by contrast, has a significantly smaller graph (1.076 nodes and 3.376 edges) and was processed much more quickly, in about 20 minutes. Considering these values, the denominator in the formula outlined above can become exponentially large, making the betweenness centrality measures infinitesimally small: in the case of Rome's graph, it translates to over 1.9 billion shortest path evaluations. For this reason, betweenness centrality measures were normalized and scaled, and only the ones above the 90th percentile were used for the graphs below.



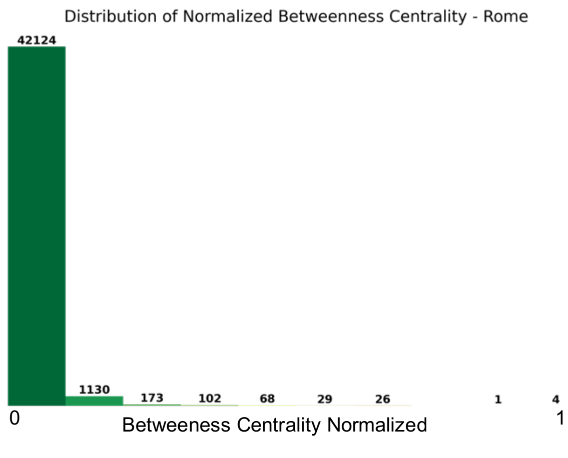


Figure 3. Betweenness centrality normalized distribution in (a) Geneva and (b) Rome.

[29] NetworkX.org

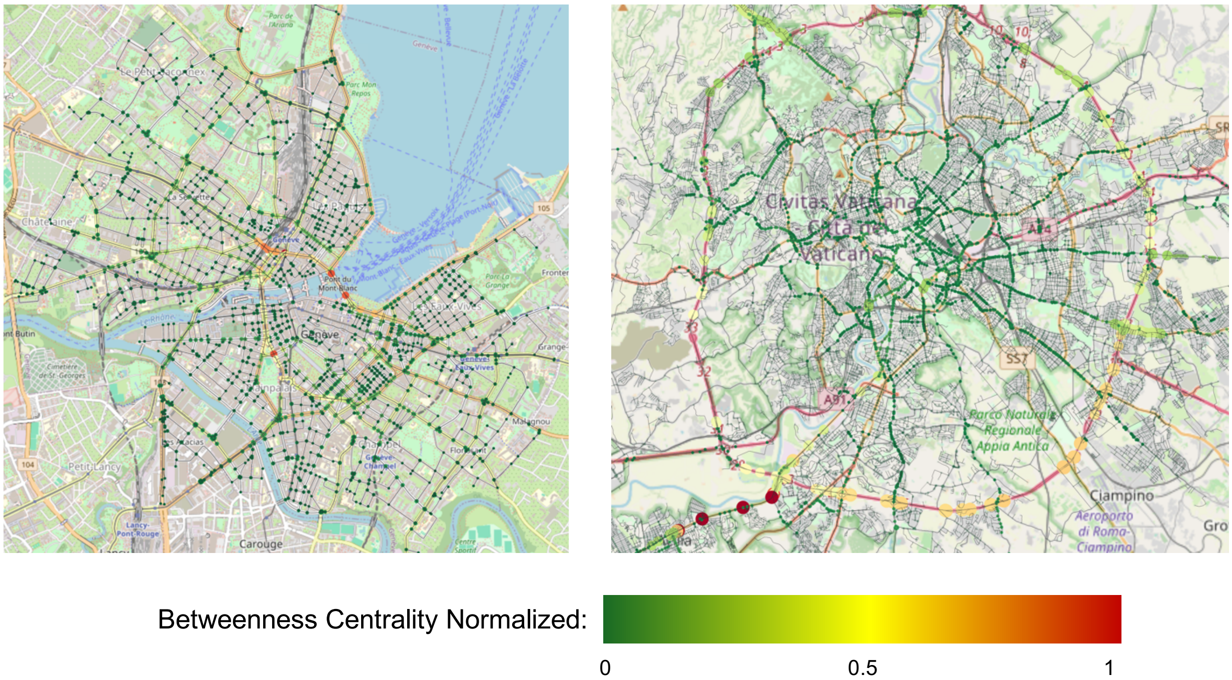


Figure 4. Visualization of top 10% nodes by betweenness centrality in (a) Geneva and (b) Rome.

Betweeness Centrality Analysis in Geneva and Rome

Figure 3 illustrates key differences in the spatial distribution of betweenness centrality across the two cities. Both Rome and Geneva exhibit left-skewed centrality distributions, with, respectively, 5 and 4 nodes having more than 0.8 betweenness centrality. Figure 4 shows where the highest betweenness points are located, marked in red and bigger in shape. In Geneva, they are key arteries for traveling within the city: Gare Cornavin, the main station receiving an outstanding number of commuters each day and therefore requiring a major degree of connectivity; the Cirque stop in Plainpalais, a vital stop in the exact center of the city, and the two junctions at the extremes of Pont du Mont-Blanc, connecting the two sides of Geneva over the lake. This centrality aligns with Geneva's compact, monocentric structure, where much of the economic and transport activity is concentrated in and around the city center, reinforcing central locations as inevitable thoroughfares.

In contrast, Rome's most central nodes southern sector of the Grande Raccordo Anulare (GRA), a peripheral orbital motorway, and, in particular, along Via Cristoforo Colombo. This reflects the polycentric and fragmented nature of Rome's urban fabric, where the historic core is heavily pedestrianized and often restricted to private vehicles. Consequently, major traffic flows and strategic connectivity tend to bypass the center, relying instead on peripheral roads, especially for paths crossing through the whole city. This suggests that Rome's congestion patterns are not only driven by radial inflows to the center but also by circumferential traffic that circulates around it, making the outer ring a crucial hub in maintaining overall network efficiency.

TomTom Data Enriching

In order to make the analysis more realistic, real traffic data were extracted using TomTom Developer API[30], from the famous homonymous satellite navigation device company. The free trial version allows to generate detailed reports on the real travel times and congestion of nodes and edges of the selected cities, limited, however, to the month of August 2024 alone, notably when the vast majority of people leaves both cities for their summer vacations. Despite the fact that such limited amount of data does not constitute a sample of observations large enough to quantify the realistic, year-round phenomenon, the data accessed via TomTom contain accurate speed limits, actual travel times and street names, that were added to the previously created graphs. The data also include statistical indicators, such as the speed harmonic average, as well as the median and mean, and average travel times, supplemented by the sample size used for their calculation. This can help making sense of the most 'central' areas of the cities, as it reflects the actual amount of cars transitated daily through each edge, but the data lack information on the time the observations were collected. Therefore, TomTom average distances and travel times will be used as a comparison for the ideal condition scenario simulation, in Chapter 5.

speedLimit	Speed limit of the segment (in km/h)
distance	Length of the segment (in meters)
shape	List of lat/lon coordinates defining the road segment geometry
streetName	Name of the street
date	Date
harmonicAverageSpeed	Harmonic average speed across samples
medianSpeed	Median speed measured
averageSpeed	Average speed measured
sampleSize	Number of samples used for statistical measures
averageTravelTime	Average travel time across the segment (*in seconds)*
medianTravelTime	Median travel time (*in seconds)*

Table 4. Feature list of edges in the TomTom dataframe.

[30] TomTom Developer

2.5 Netlogo

NetLogo is a multi-agent programming language and cross-platform modeling environment used to simulate complex natural and social systems, particularly well-suited for studying the impact of changes overtime to such systems. A major strength of NetLogo lies in its ability to simulate the behavior of hundreds or even thousands of independent "agents" acting at the same time. This allows researchers to examine how simple, local interactions at the individual level can lead to larger, emergent patterns across the system.

NetLogo models consist of three main types of agents: turtles, patches, and the observer. Turtles are mobile agents that move around and interact with each other and their environment, following a set of predefined rules, specified by the user. The environment itself is made up of patches, these are fixed grid cells that make up the two-dimensional world. Each patch can hold its own set of variables (like color, elevation, or traffic density), and turtles can sense and react to these properties as they move over them. The observer, on the other hand, is a special agent that oversees the simulation. It doesn't exist within the grid, but it can set up the environment, monitor variables, and issue commands that affect all agents at once[31].

One of NetLogo's most useful features is its interactivity, enabling users to run simulations and experiment with different parameters in real time, observing how the system responds under different conditions. To support learning and experimentation, NetLogo includes detailed documentation, tutorials, and a library of over 150 ready-made models.

Traffic modeling is one area where NetLogo has proven especially valuable. Several models have been developed to explore traffic flow, driver behavior, and congestion patterns, and are all available in the latest versions of the software:

- The **"Traffic Basic"** model, included in the standard library, simulates vehicles on a single-lane highway. Each car follows simple rules: it slows down when another car is nearby and speeds up when the path is clear;

- The **"Traffic 2 Lanes"** model adds complexity by allowing cars to change lanes, making it possible to observe how traffic jams can form and how drivers respond;

- The **"Traffic"** model introduces adjustable speed settings, the presence of law enforcement, and a special driver who always adheres to the speed limit. It also includes tools for running quantitative experiments;

- The **"Traffic Mode"** model expands the simulation to three lanes and investigates the impact of conditions like traffic lights and driver distraction on traffic flow;

[31] Janota, Aleš & Rastocny, Karol & Zahradník, Jiří. (2005). Multi-agent Approach to Traffic Simulation in NetLogo Environment - Level Crossing Model. Zeszyty Naukowe. Nr 1691. 181-188.

- The **"Gridlock"** model gives users control over traffic lights, speed limits, and vehicle numbers in real time, making it a powerful tool for exploring the dynamics of traffic systems;

- The **"HubNet Gridlock"** model extends this by treating traffic as an adaptive problem, where flow and density are constantly shifting, requiring agents to adjust accordingly.

While NetLogo has been used extensively for traffic simulations[32], most existing models simplify road networks rather than representing real city streets, making the simulations more applicable to actual transportation systems. Building on existing research and documentation, this thesis takes a different approach by **incorporating real-world urban traffic data into NetLogo and providing a more realistic way to study traffic dynamics.**

Despite Python's frameworks Mesa and Mesa-Geo's flexibility, this thesis deliberately opted for NetLogo as the primary simulation environment. This decision is grounded in both practical considerations and methodological advantages that NetLogo offers in the context of this research.

NetLogo provides a significantly lower barrier to entry in terms of environment complexity and runtime stability. During the early stages of the project, considerable time was lost managing dependency issues and version mismatches between Mesa and Mesa-Geo, and the project required frequent packages interaction, often with poor documentations; in NetLogo, the GIS extension is purpose-built for geospatial simulations, that allows direct manipulation of geographic data without external dependencies.

Another decisive factor was computational efficiency. Although Python offers more optimization options through parallelization and custom memory handling, running even moderately complex agent simulations in Mesa-Geo with hundreds of agents on realistic street networks was computationally prohibitive. The cost of initializing the environment, running pathfinding algorithms, and just loading the networks quickly became unsustainable, requiring hours to run relatively short simulations. NetLogo, by contrast, demonstrated excellent performance even with complex dual-layer networks (roads and walking paths), hundreds of agents, and dynamic routing.
Moreover, NetLogo's built-in interactivity and visualization capabilities offered an added benefit. For an application focused on urban mobility, being able to observe the simulation unfold in real time and to adjust parameters mid-run proved invaluable for both debugging and interpretation. This feature, absent or much harder to implement in Python, facilitates more intuitive model calibration and manipulation.

[32] J. J. Kponyo et al., "A Distributed Intelligent Traffic System Using Ant Colony Optimization: A NetLogo Modeling Approach," 2016 International Conference on Systems Informatics, Modelling and Simulation (SIMS), Riga, Latvia, 2016, pp. 11-17, doi: 10.1109/SIMS.2016.32.

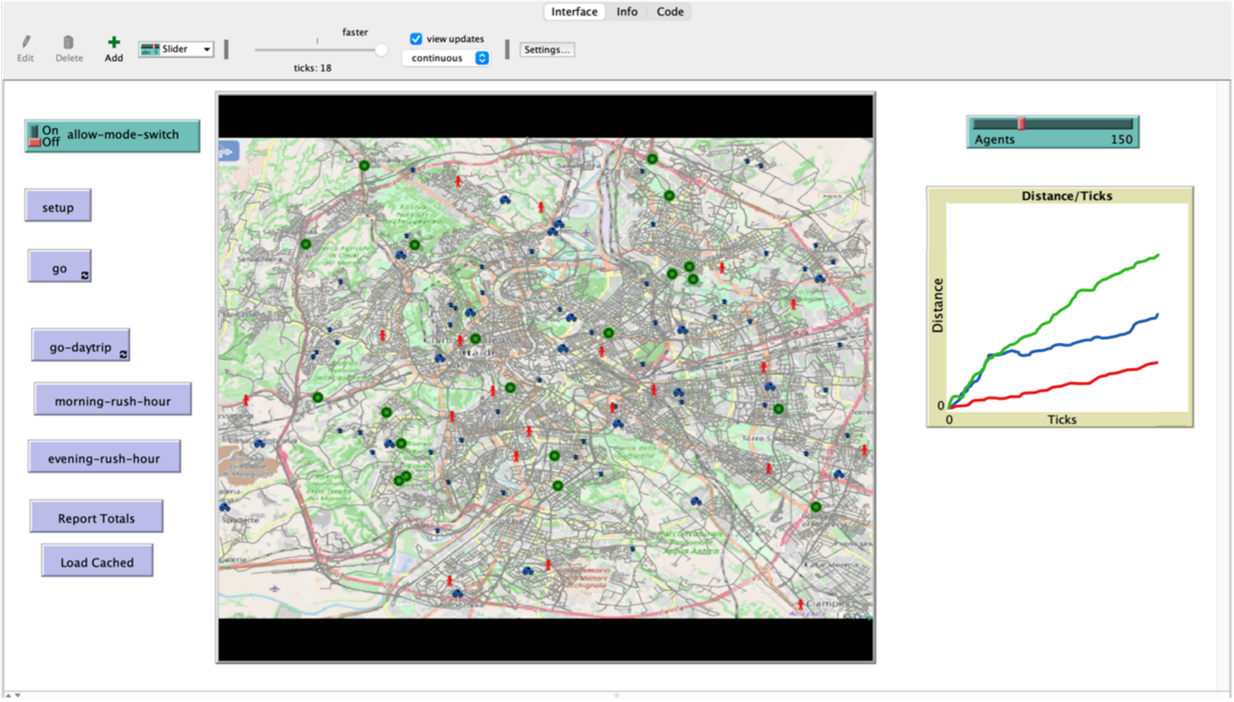


Figure 5. NetLogo Interface.
On the left side, the toggle to turn on and off mode switching and buttons to call the different interface and movement setup. The button Report Totals records the distances travelled and the button Load Cached loads a cached version of the setup network for time saving (Rome setup takes 4 days). On the right, a visualization of distances travelled per agent category.

3. Model Simulation

Before starting building the actual model, all NetLogo projects begin with importing extensions and define breeds, which form the substantial architecture for the simulation. In this case, the required extensions are `gis` and `csv`: the former allows NetLogo to interact with shapefiles, necessary to import the real-world street network extracted from OpenStreetMap, the latter enables importing data structures from pre-prepared CSV files. Extensions can be seen as Python packages, enriching its functionalities and capabilities. **Breeds** are groups of agents of the same type, similar to classes in Python.

```
breed [nodes node]
breed [searchers searcher]
breed [cars car]
breed [pedestrians pedestrian]
breed [bikers biker]
```

Nodes represent the different intersection points connecting edges, searchers are an internal, invisible breed temporarily used during pathfinding calculations to identify the shortest paths for movements, which will constitute the main logic for building rational agents: collecting the information provided by searchers, agents have complete information over the most efficient way to reach their destination, allowing them to avoid taking longer routes. The last three breeds are self-explanatory, and represent the different types of agents in the model. Each individual category of agents has its own set of rules and additional variables for modelling specific behaviours, making the simulation more realistic and modular. Taking cars an example, the nuances in their behavior are defined as cars-own `[car-path current-node waiting-time]`, where `car-path` contains the list of nodes the car must follow according to the pathfinding logic, `current-node` is a placeholder for keeping track of the position of the agent at any step and `waiting-time` is a timer used to simulate stopping at destinations, useful for later functions. In parallel, `nodes-own` defines node-specific attributes: `nodes-own [myneighbors home-node? destination-node? public-transport-stop? residential-street? node-type]`. The `myneighbors` variable lists the adjacent nodes, accessible through a single edge, while attributes featuring a question mark are Boolean flags, outputting 0 for false and 1 for true, in pure Python style. This structure mirrors the concept of class attributes in Python object-oriented programming, abstracting it for agents; this way each agent is a miniature object with its own memory and its own set of characteristics. Lastly, global variables are created, applied and visible to all agents.

```
globals [ pic-roads pthk basemap pic-walk minx miny public-transport-routes
famous-destinations car-total-time pedestrian-total-time biker-total-time ]
```

They are employed to store imported GIS datasets, load the environment, and create helper variables and functions for later use. In Python terms, these would be module-level variables: accessible everywhere, but mutable and needing careful management across agent types to model different specific own aspects. The attributes `pic-roads`, `phtk` and `basemap` are specific to the basemap uploading: the first two are NetLogo proprietary functions to load .png files, while the latter declares the variable containing the map file.

After setting up the reference tools, the first step is to upload the basemap for visual reference. Here the first pain-point came up, namely Coordinate Reference Systems (CRS). The shapefile (.shp) dataframes employed for the network structures were extracted using the native EPSG:4326 format, where spatial positions are projected on a 3D ellipsoidal Earth model. It is the standard format for GPS as it uses latitude and longitude to locate points in space, which makes it particularly reliable for computing travel times as it faithfully reproduces distances.

However, it is not ideal for a 2D representation, as its unit of measure, degrees, makes paths look distorted and stretched. The best way to address this issue would then have been to directly attach a basemap using the Contextily Python package, which retrieves tile maps from the internet for reliable visualization, projecting them on a 2D flat plane and converting the unit of measure to meters, employing the Web Mercator CRS – EPGS:3857, the one used for physical paper maps. However, NetLogo and the `gis` extension expect the previous CRS for precise mapping of coordinates, causing misalignments between the imported basemap and the network when first testing the model. In order to overcome this issue, the only feasible solution was to manually resample and stretch the basemap, using `resize-world` in NetLogo to match dimensions and tiles with the network.

Having set the basemap, driving and walking networks shapefiles were finally loaded. The walking network augments the driving one, as it contains more edges where agents can walk or bike, like riversides, parks and residential streets. Another important technical challenge is that NetLogo, considering the previous CRS requirement, interprets lengths in degrees, not meters. This implied careful adjustment of speed and distance calculations to ensure realistic mapping: real-world speeds were scaled against road lengths, which were converted keeping in mind that 1 degree of latitude corresponds to 111 kilometers, while longitude varies with latitude. After a thorough preprocessing of the measures in Python and many visual checks, all distances ensured proper correspondance between the basemap and the networks. Then, in order to let the two networks communicate between each other and to allow agents to flow through them, the create-nodes-and-links function was employed.

Checking the coordinates of each node and edges, the code below connects adjacent point in space through edges across the two networks, deleting the duplicate common ones between the two shapefiles: the walking network already contains the road networks, as pedestrians can use sidewalks located on roads. Here, from the previously declared nodes and edges-own specifics, speeds are attached to each link based on the `maxspeed` attribute extracted earlier, while residential streets are detected and tagged, influencing where home nodes will be later assigned. Walk-only paths are treated separately, since they have no speed limit, and merged with road networks where they intersect: this is done by connecting walking edges with no neighbors with the adjacent driving edges and labelling them as ‘shared’. Connecting this dual-layer network was crucial for the further steps introducing mode choice walking, cycling, public transport or driving.

```
to create-walk-nodes-and-links
  foreach gis:feature-list-of pic-walk [
    segment ->
    foreach gis:vertex-lists-of segment [
      vertex-list ->
      let previous-node-pt nobody
      foreach vertex-list [
        vertex ->
        let location gis:location-of vertex
        if not empty? location [
          let raw-x (item 0 location)
          let raw-y (item 1 location)

          let nearby-node one-of nodes with [distancexy raw-x raw-y < 0.001]

          ifelse (nearby-node != nobody) [
            ask nearby-node [ set network-type "shared" ]
            if previous-node-pt != nobody [
              create-link-between-nodes nearby-node previous-node-pt
            ]
            set previous-node-pt nearby-node
          ]

  delete-duplicates
  ask nodes [set myneighbors link-neighbors]
end
```

The public transport network integration involved some other minor technical manipulation. The Canton of Geneva is currently adopting an open data policy for its public transport data, enabling researchers to conduct studies for its optimization. All the data employed for mapping the public transport network can be accessed in the Transport Publique Genève Data Portal.[33] For the purpose of the project, the Stop and Lines .csv files were extracted. The former contained the list of all stops with their reference code and coordinates, the latter contained the list of stops driven through by each line. They were merged on the stop reference codes to obtain the list of lines passing through each stop to reconstruct to whole network. In order to avoid overly complicating the already complex network composition, stops were assigned to the nearest node, leveraging the coordinates mapping.

```
to assign-public-transport-stops
  foreach public-transport-routes [
    stop-info ->
    let stop-lat item 1 stop-info
    let stop-lon item 2 stop-info

    let nearest-node min-one-of nodes [
      distancexy stop-lon stop-lat
    ]

    if nearest-node != nobody [
      ask nearest-node [ set public-transport-stop? true ]
    ]
  ]
end
```

The only bit of data manipulation here was due to the limitation of the `csv:from-file` function that natively reads all data as strings, regardless of their formats. In order to use coordinates as numbers, they were manually casted using `read-from-string (word item x row)`, where x and y represent latitude and longitude.

3.1 Agent Initialization and Path Assignment

Once the environment (streets, walking paths, basemap, public transport) is loaded, the next step is to populate the world with agents representing urban travelers using the breeds defined earlier. To simulate realistic urban movement, agents were assigned a starting point, where they spawn, and a destination. The rationale behind the assignment leveraged the column `highway` in the original network's dataset, which contains indicators about the type of street, including 'residential', 'living street' and similar: agents don't spawn randomly, but they start their journey from 'house' locations towards predefined real places, categorized as work, leisure (gyms and parks) and shopping places. This allows great modularity potential with further

[33] TPG Open Data

computational power, possibly including useful destinations, such as hospitals, schools, airports and others.
At the setup, 50 nodes are chosen as home nodes. These are the nodes closer to edges marked as `residential`, `living street` and related.

```
ask n-of 50 nodes with [residential-street?] [
  set home-node? true
  set node-type "home"
]
```

The list of destinations was hardcoded using their coordinates and assigned to the nearest node in the network. For ease of visualization, each of the four categories was flagged with different symbols. Once all network components are loaded, agents are initialized. For each of them, one of the nodes in the home category is chosen as `start-node`, one of the destinations as `destination`, and a path between them is assigned according to the A* algorithm.

```
 set famous-destinations [
 [46.203497 6.144514 "shopping"] ;; Rue du Rhône - shopping
 [46.194178 6.142556 "shopping"] ;; Rue de Carouge - shopping
 [46.204112 6.120856 "office"]   ;; Plainpalais - university
 [46.206147 6.134604 "office"]   ;; Cornavin Station - offices
 [46.228533 6.139728 "shopping"] ;; Balexert Mall
 [46.221518 6.102301 "shopping"] ;; IKEA Vernier
 [46.207273 6.139417 "shopping"] ;; Manor Geneva
 [46.206356 6.123309 "office"]   ;; Victoria Hall - Events/Offices
                                 .
                                 .
                                 .
]
```

3.2 The A* Pathfinding Algorithm

At the heart of the simulation's mobility logic lies the A* algorithm, a cornerstone in pathfinding and graph traversal used extensively in computer science, robotics, and transportation modeling. Introduced by Hart, Nilsson, and Raphael in 1968, A* improves upon earlier search algorithms like Dijkstra's by introducing a heuristic, a way of estimating the cost to reach the goal from any given point, thus guiding the search more intelligently[34]. In a city context, one might imagine it as the equivalent of a pedestrian glancing at a map and saying, "This route looks fastest not just because it's short, but because it follows wide roads and avoids hills." It's a balance between what we know and what we expect.

[34] Hart, P. E., Nilsson, N. J., & Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. IEEE Transactions on Systems Science and Cybernetics, 4(2), 100–107.

Formally, the algorithm minimizes a cost function $f(n) = g(n) + h(n)$ where:

- f(n) is the total estimated cost of the cheapest solution path that goes through node n;
- $g(n)$ is the known cost from the start node to node n (the "travel so far");
- $h(n)$ is the heuristic estimate of the cost from n to the goal (the "best guess" of the travel ahead).

In this model, $g(n)$ is computed based on the real travel distance, adjusted by the road's speed limit, simulating travel time rather than geometric distance. This makes the cost more grounded in how real people make route decisions. For example, a highway might be longer in meters than a side street, but its higher speed limit makes it a faster, and thus preferred, option. The heuristic $h(n)$ is calculated using Euclidean distance, which, while a simplification, serves as a mathematically admissible estimate (i.e., it never overestimates the true cost), ensuring the algorithm remains both optimal and complete[35].

```
to-report A* [#Start #Goal]
.
.
.
  ask #Start [
    hatch-searchers 1 [
      set localization myself
      set memory (list ([who] of localization))
      set cost 0
      set total-expected-cost (cost + heuristic #Goal)
      set active? true
    ]
  ]
.
.
.
  while [not any? searchers with [localization = #Goal] and any? searchers with
[active?]] [
    ask min-one-of (searchers with [active?]) [total-expected-cost] [
      set active? false
      let this-searcher self
      let Lorig localization
      ask ([link-neighbors] of Lorig) [
        let connection link-with Lorig
        let c ([cost] of this-searcher) + [link-length] of connection
        if not any? searchers-in-loc with [cost < c] [
          hatch-searchers 1 [
            set localization myself
            set memory lput ([who] of localization) ([memory] of this-searcher)
            set cost c
            set total-expected-cost (cost + heuristic #Goal)
            set active? true
            ask other searchers-in-loc [die]
.
.
.
```

[35] Pearl, J. (1984). Heuristics: Intelligent search strategies for computer problem solving. Addison-Wesley.

The implementation in NetLogo is both elegant and efficient. A temporary, invisible breed called searchers acts as the expanding wave of intelligence from the source node. These searchers function almost like neurons firing across a spatial network, testing routes, remembering their cost ($g(n)$), and projecting their potential ($f(n)$). At each iteration, the algorithm selects the most promising node, that is, the one with the lowest estimated total cost, and expands it, spawning new searchers into neighboring nodes if those paths improve upon existing alternatives. Once the goal node is reached, the optimal path is backtracked from the searcher's memory, passed back to the agent, and stored as its `car-path`, `ped-path`, or `biker-path`.

This mechanism creates a boundedly rational system in which agents behave with limited, localized knowledge but pursue clearly defined objectives. They cannot see the whole city, but they can make decisions that are "good enough" given the available data, a paradigm aligned with the classical behavioral economics tradition[36]. This is crucial for urban simulations, where the complexity of the environment makes full omniscience both unrealistic and computationally impractical.

In metaphorical terms, one could imagine each agent as a commuter waking up, checking Google Maps, and planning their route based on what they know: estimated times, traffic speeds, and road types. They don't need to explore every corner of the city, they trust a smart shortcut. But unlike in real life, where people may choose suboptimal routes due to habit, misinformation, or mood, agents here are purely rational. That's what makes this model such a powerful contrast to actual traffic behavior: it gives us a baseline of how urban flow could look if everyone made efficient choices. And comparing this ideal to real-world congestion later in the thesis provides valuable insights on the difference complete information on traffic and rational pathfinding make, exemplifying the cost of human unpredictability in simulated realistic scenarios.
The code above was used to model the A* pathfinding algorithm. Initially, a validation check ensures that a goal node is defined and reachable for all agents. Once the validation is passed, a searcher agent is created at each starting point. Searchers hold a list of identifier variables, namely their localization, or the node they're currently on, a memory of the nodes they visited, the total expected cost, set to 0 at the start of the travel, and a Boolean to check if they already reached their goal or they're still active. Active searchers reach their destinations by iteratively selecting the searcher with the lowest total expected cost among their neighbor nodes, `ask min-one-of (searchers with [active?]) [total-expected-cost]`. For each neighbor, a new searcher is spawned only if no existing searcher at that node has a lower cost. The new searcher inherits the memory and cumulative cost from its predecessor, updates its localization, recalculates the total expected cost, and sets its active status to true. Sub-optimal searchers, those with a cost higher than the chosen one, are killed: `ask other searchers-in-loc [die]`.

[36] Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 69(1), 99–118.

3.3 Agent Movement Logic

Once agents are spawned, assigned a starting node, and given a destination, the logic of the simulation truly manifests, translating static data into dynamic behavior. Movement in NetLogo is not continuous, but discretized into ticks, each tick representing one unit of simulation time. While ticks represent simulation time steps, their real-world equivalent (seconds, minutes) can be interpreted flexibly depending on calibration needs. In each tick, agents check their environment, update their state, and take a small step toward their target. This logic is structured through a series of move-agent procedures, tailored to each breed.
There are two main procedures handling movement:

- `move-agent`: used for general simulations;
- `move-daytrip-agent`: a more nuanced version used of the first function, imitating a classic daytrip path to explore the city, introducing pauses at scenic or destination nodes.

Both follow a very similar logic: they retrieve the next node from the agent's path and attempt to move the agent toward that node. If the agent gets close enough (within a 0.5 NetLogo unit radius), it "snaps" to the new node, updates its current-node variable, and proceeds to the next step of the path.
At its core, the movement logic can be broken down as follows:

```
let next-node-who item 0 path
    let next-node turtle next-node-who
```

This retrieves the next node from the path, and references it using NetLogo's who identifier system (analogous to a unique node ID). We then determine a movement speed (move-speed), which varies by agent type.

For cars, speed is based on the `link-maxspeed` of the road segment connecting the current node to the next. However, this speed is scaled to simulate real-world traffic frictions such as stops, turns, or lights. The scaling factor (0.8 for general movement, 0.6 for daytrips) is a crucial modeling assumption: while a road might be marked at 50 km/h, urban environments rarely allow constant maximum-speed driving. This accounts for waiting at intersections, pedestrians crossing, or simply acceleration/deceleration patterns.

```
if agent-type = "car" [
      if connecting-link != nobody [
        let road-speed [link-maxspeed] of connecting-link
        if rush-hour-mode = "morning" [
          set move-speed (road-speed / 50) * 0.38
        ]
        if rush-hour-mode = "evening" [
          set move-speed (road-speed / 50) * 0.35
        ]
        if rush-hour-mode != "morning" and rush-hour-mode != "evening" [
          set move-speed (road-speed / 50) * 0.8
        ]
      ]
```

This converts a 50 km/h speed into a normalized scale where 1 unit = "full speed", then scales it by 0.8. The scaling factors for the morning and evening rush hour scenarios simulations are defined from the traffic reports in Chapter 4.

Pedestrian logic introduces mode differentiation: some pedestrians walk entirely, while others use public transport, a decision randomly assigned at setup with a 50% chance. Randomness introduces agent heterogeneity, an essential element in representing real-world urban dynamics where not all agents behave identically. When pedestrians hop on buses, their speed increases to match the speed limit of the road they are on.
Bikers are given a constant speed of 0.5 units per tick. This sits between the walking speed (0.2) and scaled car speed (~ 0.6 - 0.8), based on data from Geneva's bike-sharing system, which reports average inner-city biking speeds around 15 km/h[37].
Once speed is determined, the agent orients toward the next node and moves. The model uses NetLogo's built-in turtle movement logic (fd = "forward"). Then, if the distance to the next node is below 0.5 units, it "lands":

```
face next-node
fd move-speed

if distance next-node <= 0.5 [
  move-to next-node
  set current-node next-node-who
```

This update also checks if the path is empty, creates a new working one using the A* algorithm, simulates a new daily trip, or reroutes.

In the move-daytrip-agent version, there's an extra twist: agents pause at destinations (e.g., parks, shopping centers, landmarks) before continuing. A waiting-time variable controls this, triggered when the agent lands on a node marked with a node-type, simulating the idea that people don't just move, but linger, explore, and return.

```
to move-daytrip-agent [path agent-type]
  ifelse waiting-time > 0 [
    ;; Still waiting at scenic location
    set waiting-time waiting-time - 1
  ] [
    ;; Otherwise normal movement

if [node-type] of next-node != "" [
          set waiting-time 10 + random 20 ;; 10 to 30 ticks
]
```

This mechanic adds both realism and variability to the simulation, giving a more human-like rhythm to the agents' behavior. From a human-centered perspective, each agent mimics a person in a city: they wake up at home, glance at a map or app,

[37] TPG VéloPartage

pick the best route to their goal, and head out. Their movement is rational but not robotic. Some take bikes. Some hop on trams. Some drive. Once at their destination, they stay a while, window-shopping, attending a class, or just sitting by the lake, and then move on. By embedding this logic in the simulation, the aim is not just to simulate routes, but to simulate routines. And this is where NetLogo's agent-based framework shines: instead of traffic being treated as a fluid or a queue, it becomes the emergent result of thousands of tiny decisions - each path calculated, each turn taken, each pause intentional.

For simulating rush hours scenarios, most congested points were hard-coded using their coordinates from Figures 8 and 11, together with nodes in an area of radius of 0.05 degrees from them: `ask nodes with [distancexy ([xcor] of center-node) ([ycor] of center-node) < 0.05]`.

```
to decide-switch-if-congested
  let path-nodes map [n -> turtle n] car-path
  if any? path-nodes with [member? self congested-nodes] [
    if allow-mode-switch [
      ;; 90% switch to walking, 10% to biking
      ifelse random-float 1.0 < 0.9 [
        hatch-cars 1 [
          set shape "person"
          set color red
          set size 12
          set ped-distance-traveled car-distance-traveled
          set current-node [current-node] of myself
          move-to myself
          assign-ped-path
        ]
      ] [
        hatch-cars 1 [
          set shape "wheel"
          set color green
          set size 12
          set biker-distance-traveled car-distance-traveled
          set current-node [current-node] of myself
          move-to myself
          assign-biker-path
        ]
```

With this chunk of code, car agents that have congested nodes on their path are allowed to switch mode of transportation, with a likelyhood facture of choosing the bike dependent on the city (10% of switching drivers will ride a bike in Geneva, 5% in Rome). The switch happens with agents mutating category and getting assigned either walking or pedestrians features and paths.

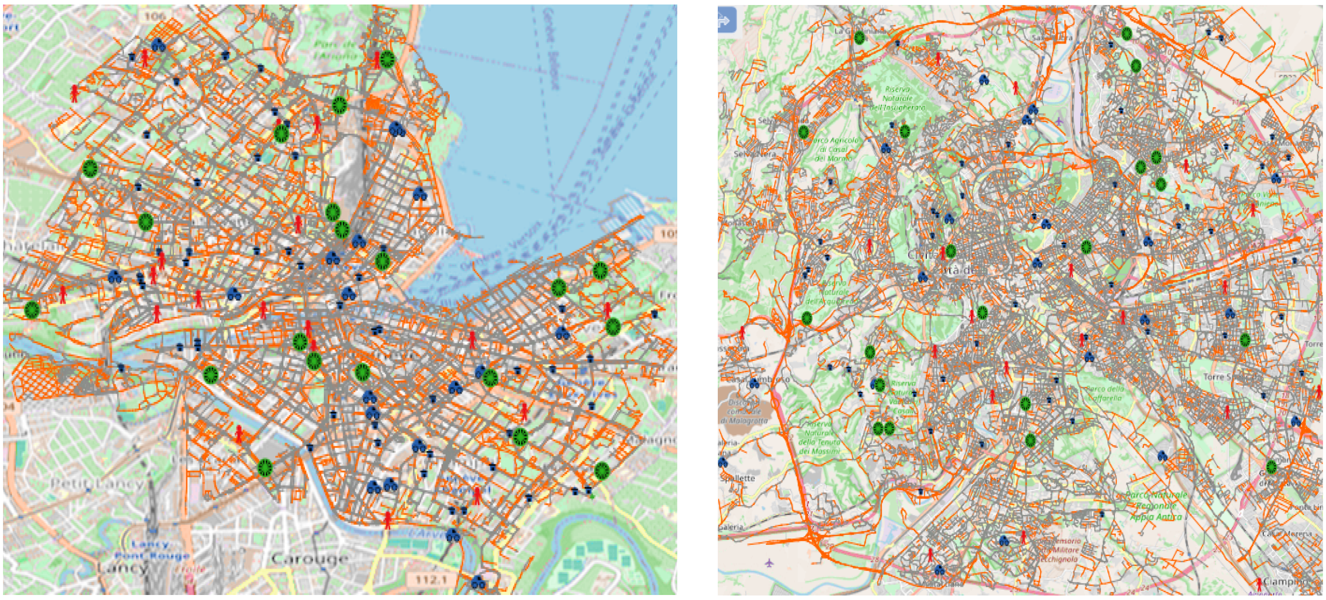


Figure 6. Geneva (a) and Rome (b) networks once all agents, start and destination nodes are generated. The red ‘person’ symbols represent pedestrians, the green ‘wheel’ symbols represent bikers, the blue ‘car’ symbols represent cars. The small blue icons represent the different categories of destination nodes; making icons bigger and of different colors overloads the model, increasing the computational time for the simulation by 20%, resulting in an additional hour for loading Geneva network and a whole day for Rome.

- *houses*
- *public transport stops*
- ★ *shopping places*
- *gyms and leisure*
- ▲ *work places*

4. Traffic Background

To dive deeper into the cross-analysis between actual and simulated data, it is necessary to understand the current and past traffic and urban transportation trends in the two cities under investigation. Despite being different in many dimensions, especially the number of inhabitants and the expansion of the metropolitan area, they essentially share similarities in terms of traffic congestion and gridlock.

4.1 Geneva Urban Mobility: Traffic Patterns and Modal Split

Geneva consistently ranks as one of the most congested cities in Switzerland, and indeed, across Europe. Despite its relatively compact size and high public transport usage, the city’s road network remains under considerable pressure. In recent years

(2020–2025), Geneva's transportation environment has been defined by a paradox: a highly multimodal society, yet persistent traffic bottlenecks. Nearly half of all trips by Geneva residents are undertaken on foot, about a third by private vehicles, and roughly 14% using public transport. Nonetheless, strategic arteries such as the Pont du Mont-Blanc continue to experience daily gridlock, particularly during peak commute hours.

This situation provides a valuable backdrop for this project. If even a city where walking is dominant struggles with car congestion, it raises crucial questions about behavior, rationality, and network strain, precisely the elements that an agent-based model can help unpack. In fact, understanding Geneva's specific mobility structure is crucial before testing simulated changes: small shifts in modal share here could ripple through the system in unexpected ways, due to the tightness and sensitivity of the urban fabric.

The 2021 Swiss Mobility and Transport Microcensus shows Geneva's modal split to be unusually favorable to walking: about 49% of all trip stages are made on foot. This is higher than the Swiss national average (41%) and only slightly down from 2015 (52%)[38]. Such a walking culture is rooted in Geneva's dense urban layout, its compact city center, and pedestrian-friendly infrastructure. These characteristics make short trips feasible without a vehicle and foster a kind of localized mobility that is quite distinct from sprawling urban forms elsewhere.

Private motorized transport (cars and motorcycles) accounts for around 31% of trip stages, a share significantly lower than the Swiss national average of about 39%. Within this, solo car driving represents roughly 20% of trips, while being a car passenger covers about 8%, and motorcycles or mopeds add another small fraction. Notably, while Geneva's car usage is relatively modest compared to other cities, it remains a major contributor to congestion hotspots, especially given that a large volume of regional and cross-border traffic must pass through a limited number of lake crossings and downtown corridors.

Public transportation, including trams, buses, and regional trains like the Léman Express, carries about 14% of trips, with an average of 742,000 boarding passengers daily[39]. This share dipped slightly in 2021 compared to pre-pandemic levels (~16% in 2015), mainly due to COVID-19 disruptions, but rebounded strongly by 2022–2023, reflecting the resilience of Geneva's transit system. Importantly, many Geneva residents already own transit passes or bikes, making them flexible travelers able to switch modes depending on time, weather, or incentives, a behavioral trait that agent-based modeling can directly simulate.

Cycling, although historically limited, has been growing. In 2021, about 6% of trips were made by bike (combining traditional bikes and e-bikes), double the share recorded in 2015. The rise of e-bikes and the expansion of dedicated bike infrastructure during the pandemic have helped accelerate this shift. While still a small share compared to walking or driving, it represents an essential evolving trend:

[38] La Mobilité des habitants du canton de Genève en 2021
[39] TPG Open Data

Geneva's mobility system is becoming more multimodal and responsive to policy nudges.

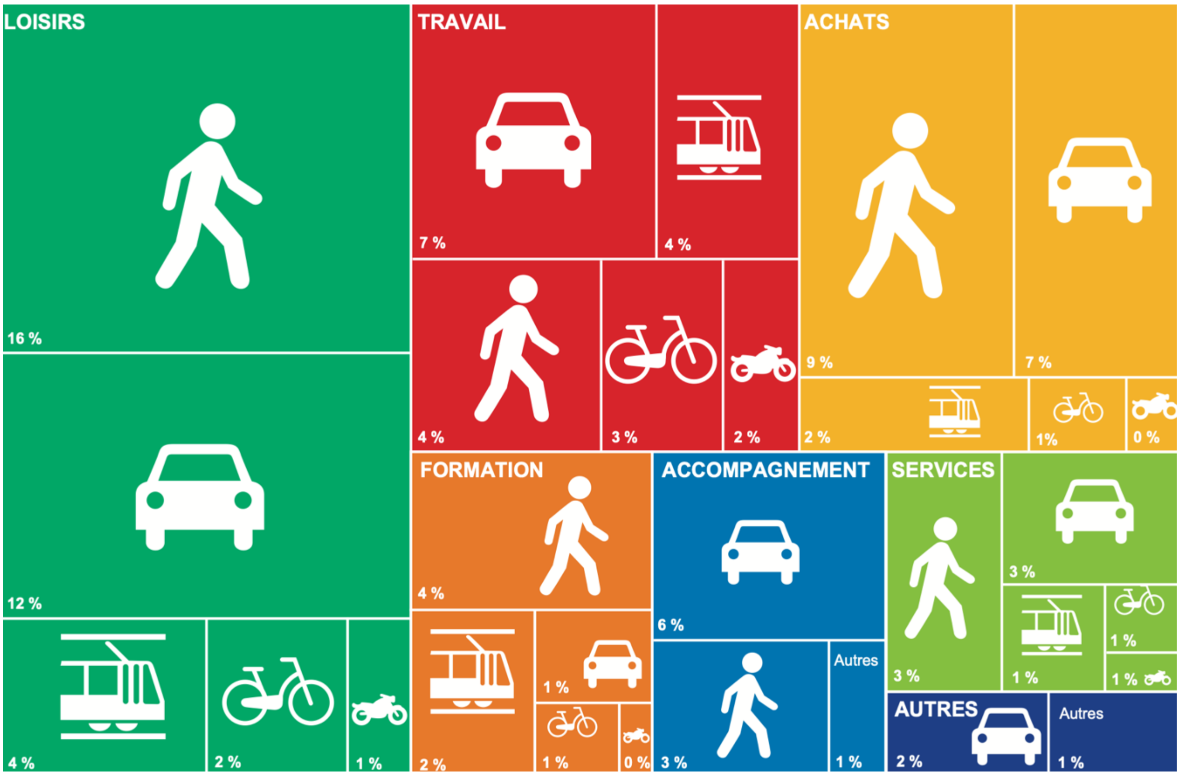


Figure 7. Distribution of transport mode with reason. Source: La Mobilité des habitants du canton de Genève en 2021

In aggregate, the city's modal split stands at approximately 50% walking, 30% private motorized transport, 15% public transport, and 5% cycling. From a modeling standpoint, this mixed-use environment is vital: agents cannot be simply assigned one default behavior, but must reflect diverse preferences and possibilities. The dynamic interactions between these modes and their sensitivity to infrastructure changes are central to replicating Geneva's real-world mobility flows in simulation.

4.1.1 Congestion Hotspots and Temporal Patterns

Despite its favorable modal shares, Geneva remains one of the most congested cities in Europe. In 2024, drivers lost an average of 69 hours annually in traffic jams, making it the worst figure in Switzerland. Peak travel times typically see a 30% increase journey duration compared to free-flow conditions, with central crossings like Pont du Mont-Blanc and Pont de la Coulouvrenière acting as recurrent choke points. Around 80,000 vehicles daily cross Pont du Mont-Blanc alone, funneling regional and cross-border commuters through a few constrained bottlenecks[40].

[40] TomTom Traffic Index Switzerland 2024

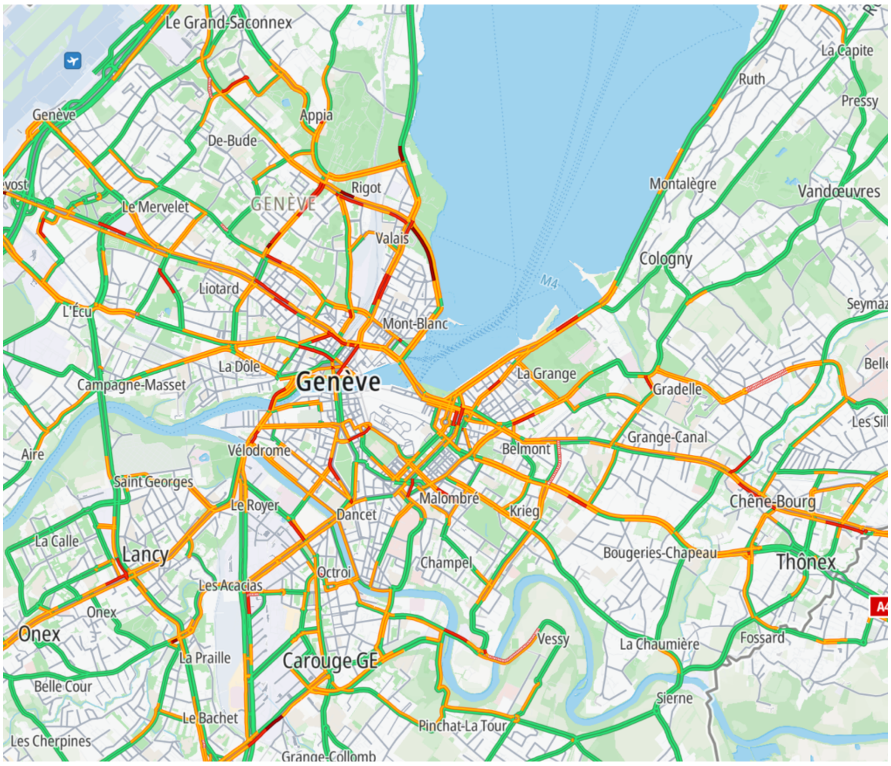


Figure 8. Geneva Traffic Congestion on a Wednesday at 6pm.
Source: [TomTom Geneva Real Time Traffic Report]

The causes of this congestion are structural. Geneva's geography, bounded by the lake, the Rhône river, and the French border, inherently channels traffic into a handful of critical corridors. Local commuting, cross-border flows (over 100,000 workers daily from France), and tourism-related movements converge, particularly during weekday rush hours (7–9 a.m. and 5–6 p.m.)[41]. During these windows, typical travel times across the city can increase by 50% to 70% compared to free-flow conditions.

TomTom traffic data, among other sources, confirms these patterns. During evening rush hour, delays of up to +71% have been recorded in Geneva, comparable to larger metropolitan areas such as Hong Kong or New York. Interestingly, the morning peak tends to be slightly broader and less sharp, possibly due to a staggered start among different sectors (e.g., construction workers starting earlier, office workers later). This particular temporal structure also reflects Geneva's unique economic fabric, with many international organizations and service-sector employers concentrated downtown.

Midday traffic volumes are moderate but still substantial, especially around major commercial areas. A smaller "lunch peak" is often noticeable between 12:00 and 1:30 p.m., driven by people making short errands, going to lunch, or moving between work meetings. On the other hand, late evening and nighttime traffic tends to be light, a trend reinforced by Geneva's introduction of a citywide 30 km/h nighttime speed limit in 2022 to reduce noise pollution.

[41] Office Cantonal de la Statistique

Weekend traffic patterns are somewhat different. Saturdays typically see a spike in shopping-related travel, especially around malls like La Praille or along major commercial streets like Rue de Carouge. Sunday traffic is lighter overall, although airports, lakeside promenades, and tourist sites can still generate localized jams. Seasonal events, such as ski season weekends or summer festivals, add further variation: during these times, Geneva's outskirts, particularly access roads to France or to the mountains, can experience unusually severe congestion.

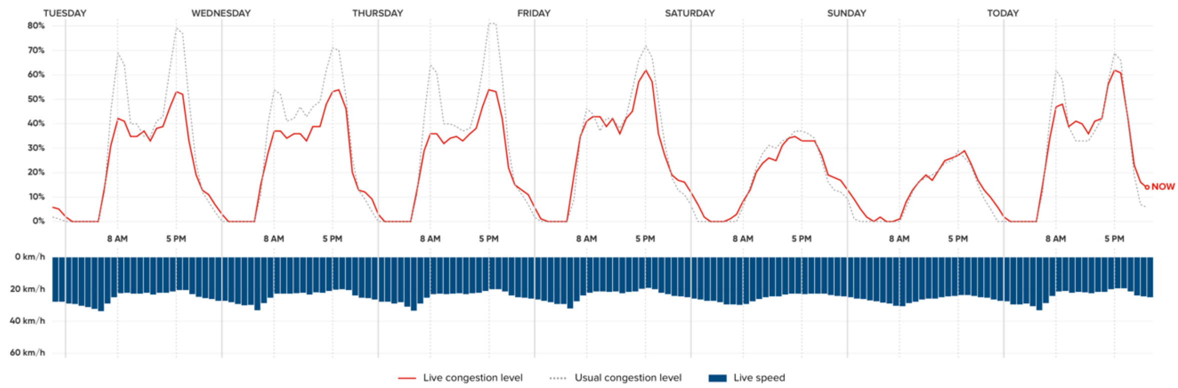


Figure 9. Weekly congestion and average speed per hour in Geneva.
Source: [TomTom Geneva Traffic Index]

From the perspective of agent-based modeling, these temporal dynamics are critical. Agents should not behave identically throughout the day or week: instead, they must adapt to fluctuating conditions, representing morning versus evening travel, weekday versus weekend behavior, and even seasonal shifts. In the future development of this model, the introduction of time-based policies (e.g., peak-hour restrictions, congestion pricing) could be simulated by adjusting agent preferences or route choices depending on the current simulation tick, allowing the model to test interventions not just spatially, but temporally as well.

4.1.2 Recent Policy Changes and Interventions (2019–2025)

Over the past five years, the Geneva Canton has rolled out a series of policy interventions aimed at tackling its persistent traffic congestion and aligning mobility practices with broader environmental goals. These actions range from expanding non-car infrastructure to regulating road use more strictly, while making significant investments in public transport. As Geneva's Cantonal Climate Plan emphasizes, the objective is not simply to ease traffic, but to reshape the system toward more sustainable and resilient mobility patterns[42]. This broader vision fits directly into the systems view underpinning this thesis.

[42] My Climate Geneva

One of the most visible changes has been the surge in cycling facilities across the canton. Following intense public support expressed in a 2018 referendum, Geneva launched the *Plan d'Actions Mobilité Douce 2019–2023*, accelerating investments into cycling and walking infrastructure. Among the most notable projects is the *Voie Verte*, a continuous active-mobility corridor partially built along a former railway line, opened in stages by 2021[43].

Additionally, the construction of protected two-way cycle tracks along key arteries such as Quai du Mont-Blanc and Quai Wilson has, for the first time, created a safe north-south bicycle route parallel to the heavily congested lakeside roads. Intersections have been reengineered to prioritize cyclists, and contra-flow bike lanes have become common downtown.

The outcomes are encouraging. By 2021, the modal share of cycling had doubled to around 6%, with city officials reporting traffic counts on some lanes more than doubling. However, the transition has not been without tensions. Some lanes were created by reallocating car lanes (notably during the COVID-19 pandemic), sparking backlash from driver associations who claimed that these changes exacerbated congestion. Authorities have since adopted a balancing strategy, retaining successful bike lanes while adjusting others in response to traffic pressures.

From a modeling perspective, this shift underlines the necessity of simulating modal shift dynamics carefully: expanding cycling infrastructure does not simply displace drivers instantly, but gradually reconfigures trip choices over time, influenced by perceived safety and convenience.

At the same time, Geneva has made major moves to strengthen public transport, with the most transformative being the opening of the *Léman Express* in December 2019. This cross-border commuter rail network has added significant capacity, linking French neighboring towns like Annemasse and Annecy and Swiss suburbs like Coppet directly to Geneva's central stations.

In parallel, extensions to the tram network, such as the cross-border extension of Tram 17 to Annemasse and the 2022 Tram 15 extension to Plan-les-Ouates, have expanded the catchment area for high-quality transit. Alongside these projects, the number of park-and-ride (P+R) facilities was expanded to facilitate multimodal commuting.

Despite the disruption of COVID-19, public transport ridership has rebounded strongly: by 2023, Geneva's public transport agency (TPG) reported daily boardings approaching pre-pandemic levels, with user satisfaction rates exceeding 80%[44].

Geneva has also introduced smarter traffic management strategies. Intelligent traffic lights now adjust in real-time to flow conditions on major corridors like Route de Meyrin, while ramp metering systems regulate the influx onto the autoroute. The adoption of a blanket 30 km/h speed limit at night (since 2022) fits into a broader trend of using speed management not only for safety and noise reduction, but

[43] Plan d'Actions de la Mobilité Douce 2019-2023
[44] Bus Tram Genève - Histoire & Actualité de la mobilité Genevoise

potentially for congestion smoothing by limiting stop-start behavior. Although controversial, some business groups fear negative effects; the international experience suggests that lower urban speeds can sometimes improve flow reliability without significantly impacting travel times. It is noteworthy, however, that Geneva has so far avoided implementing more aggressive demand management strategies such as congestion pricing. Although proposals, like tolling the Mont-Blanc Bridge, have been floated, political resistance remains high.

4.1.3 Expert Analyses and Future Traffic Projections

When looking at Geneva's congestion challenges through the lens of expert studies, a clear message emerges: the current situation is the product of deep structural forces and, without bold, coordinated action, things are set to get worse. It's not just about slow cars in narrow streets; it's about how the city and the wider region have evolved, and how different layers of policy and behavior interact over time.

Understanding this systemic view is critical not only for policy but also for building meaningful agent-based models. In a city like Geneva, where local conditions reflect decades of urban, economic, and cross-border dynamics, capturing future scenarios demands that models reflect more than just traffic volumes: they must encode underlying drivers of change.

Experts agree that congestion in Geneva is not primarily a result of inefficient traffic management or "bad" driver behavior. Instead, it stems from broader patterns: regional economic growth, persistent housing shortages, and the resulting “pendular dependency” on commuting across long distances.

Lorenzo Quadranti from OFROU (Federal Roads Office) points out that across Switzerland, traffic on major highways, including Geneva's bypass, has grown much faster than the population[45]. Economic prosperity brought higher mobility demand, but infrastructure expansion hasn't kept pace. Geneva's case is even more acute because high real estate prices have pushed thousands of workers to live outside the canton, many in neighboring France, thus locking in long daily commutes.

Urban sociologist Alexis Gumy (EPFL) emphasizes that Geneva's urban sprawl into France means that many commuters have no realistic alternative to driving. Until housing supply near jobs is improved and better regional transport is built, congestion will remain deeply entrenched[46].

The patterns and interventions observed in Geneva's traffic system over the last few years offer clear lessons, not just for policymakers, but also for researchers aiming to model urban transport systems more accurately. One thing becomes obvious when looking at Geneva as a living system: congestion is not simply a technical failure. It's the emergent outcome of millions of small individual decisions, shaped by

[45] Office Fédéral des Routes Report Annuelle du Trafic 2023
[46] Laboratoire de Sociologie Urbaine de l'Ecole Polytechnique fédérale de Lausanne

infrastructure, incentives, habits, and external shocks. In order to truly understand or change these outcomes, both planning and modeling approaches must embrace this complexity. Building a meaningful ABM for Geneva is not just about replicating congestion levels; it's about capturing *why* and *how* people move the way they do, and how small shifts at the individual level ripple through the whole system.

4.2 Rome Traffic Patterns and Urban Mobility

In Rome, the dominant presence of private vehicles continues to define the city's mobility landscape. With 64 cars for every 100 residents, one of the highest motorization rates in Europe, Rome far outpaces cities like Milan (49), Madrid (46), London (31), and Paris (25) in car ownership[47]. Unsurprisingly, private transport overwhelmingly shapes the modal split: around 59% of daily trips are made by car or motorbike, according to the latest Sustainable Urban Mobility Plan (PUMS). Public transport captures about 21–22% of trips, mainly through buses, trams, and the metro system, while active modes, walking and cycling, account for roughly 18% and a marginal 1–2%, respectively[48].

This distribution clearly illustrates Rome's deeply rooted car culture, especially compared to cities like Paris or London, where cycling and public transport have a more substantial share. Micro-mobility solutions like e-scooters have emerged quickly since 2019, becoming visible especially in central neighborhoods, yet they still represent a tiny proportion of trips (around 1% or less).

The structure of the city itself reinforces this pattern. Rome's sprawling metropolitan footprint, limited high-capacity transit coverage, and a fragmented network of radial roads naturally encourage private car use. Motorbikes and scooters, about 8% of the modal split, offer an agile solution to navigate traffic and tight urban spaces.

While Rome's public transport system, composed of buses, two metro lines (A and B), a partially operational Line C, urban railways, and trams, handles about 1.3 million trips per weekday, its effectiveness is often constrained by chronic reliability issues. Compared to other European cities, the underground network in Rome really represents a 'black sheep' in the category: in the Italian Capital, only 60,6 km are covered through 73 stations, as shown in Figure 10. To put it into context, Milan has 113 stations serving 96,8 km; the underground network in Paris runs for 215,6 km, with 302 stations. Worsening the scenario even further, 47% of the rail means of transport were established more than 15 years ago. The extensive use of cars feeds into a cycle of congestion that discourages alternatives: limited public transport coverage leads people to drive, and the more congested the roads become, the harder it is for other modes to gain ground.

[47] Ecosistema Mobilità - Roma: Mobilità urbana, criticità e prospettive
[48] Urban Logistics as an On-Demand Service

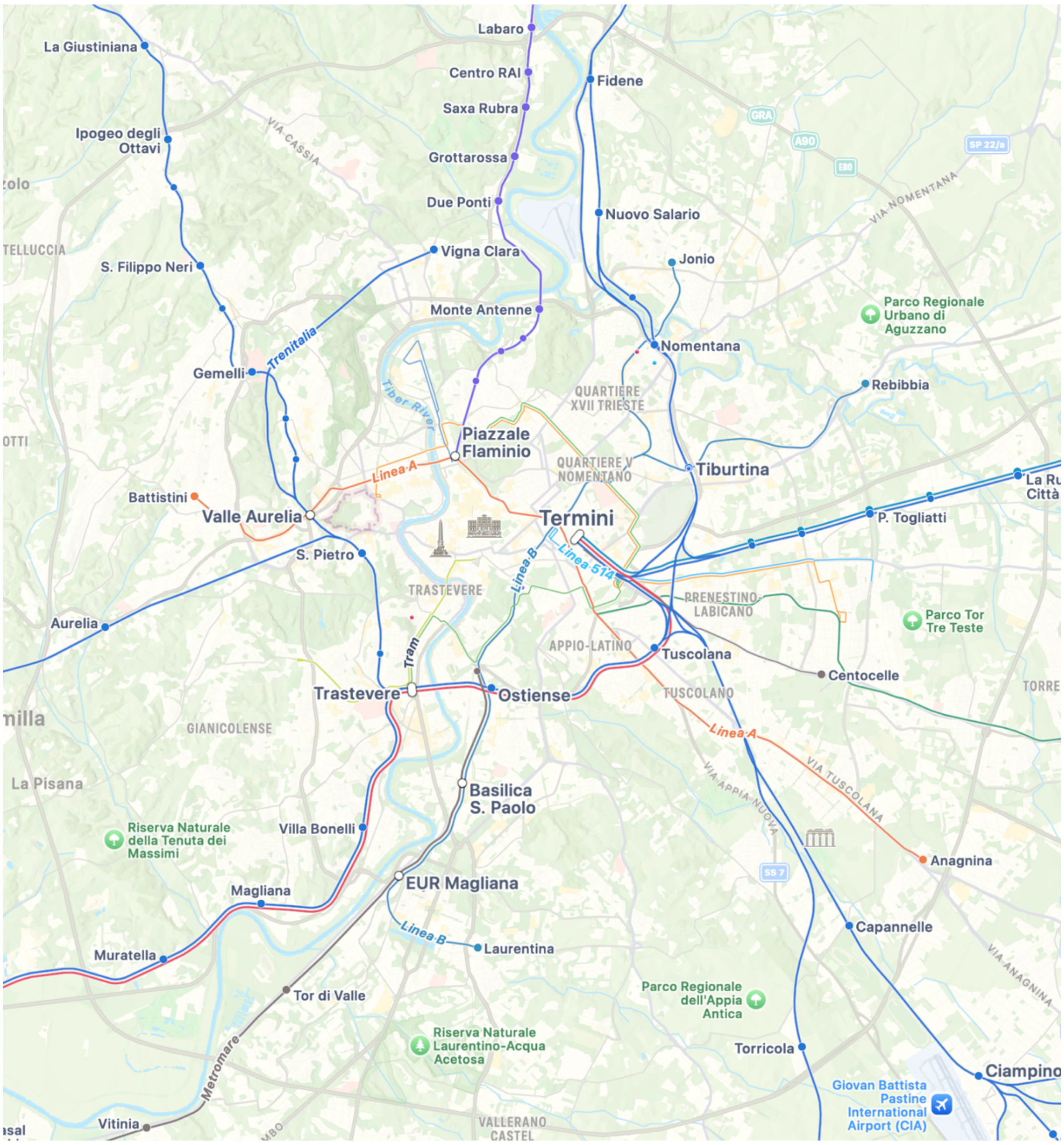


Figure 10. Rome public transportation map (buses excluded). Large part of the metropolitan area remains unserved. Source: Apple Maps, Public Transport Level.

On the active mobility side, walking retains a meaningful role, particularly within the historic center and dense neighborhoods. However, the city's peripheral areas, characterized by sprawl and car-oriented urban forms, remain inhospitable primarily to pedestrians. Cycling continues to lag behind, hindered both by infrastructural deficits (few protected bike lanes) and the city's challenging topography, cobblestones, hills, and chaotic traffic all pose barriers.

That said, there have been signs of gradual change in recent years. The number of electric scooters available for rent exploded to around 14,500 by 2022, and small investments in bike lanes hint at an emerging micro-mobility culture[49]. However, the incremental growth of micro-mobility options didn't sit right with the already chaotic Roman transportation picture, forcing the municipality to limit the service exclusively to 3 companies, reducing the number of e-scooters to 9,000[50] as of September 1, 2023. Yet, despite these developments, private cars continue to dominate, feeding congestion levels and locking the city into a self-reinforcing pattern: the lack of attractive alternatives sustains high car use, which in turn further discourages a modal shift.

4.2.1 Congestion Hotspots and Bottlenecks

Rome is consistently ranked among Europe's most congested cities, and anyone who has spent time navigating its streets quickly understands why. Even before the pandemic, in 2019 Roman drivers were losing around 166 hours a year stuck in traffic, the worst figures in Europe and the third in the world, only behind Bogota and Rio de Janeiro[51]. Although travel patterns shifted temporarily in 2020 and 2021, congestion by 2022–2023 had largely rebounded to pre-pandemic levels.

The city's complex road network, an often chaotic blend of ancient, medieval, and modern layers, creates a geography of congestion that is anything but uniform. Traffic bottlenecks can generally be divided into two main categories: those in the historic core, and those on the city's outer beltways and radial roads.

In the center, the narrow medieval streets of the Centro Storico, combined with intense tourist activity, naturally limit traffic capacity. Despite the existence of Limited Traffic Zones (ZTLs) designed to restrict car access, congestion remains a daily reality, especially along the Lungotevere (the boulevards flanking the Tiber River), around Termini Station, and at major intersections like Porta Maggiore. Key arteries such as Via del Muro Torto and Viale del Circo Massimo regularly slow to a crawl during peak hours. Similarly, the bridges across the Tiber, including Ponte Vittorio Emanuele and the Ponte Sisto area, serve as critical chokepoints, concentrating flows and generating frequent bottlenecks.

Adding to the complexity, construction projects, particularly those tied to the ongoing extension of Metro Line C near the Colosseum, have occasionally caused major detours and local tailbacks. Tourist sites like the Vatican and Piazza Venezia attract constant streams of visitors and create traffic surges that ripple outward into surrounding neighborhoods. Even where access to the historic core is restricted, traffic often queues just outside the ZTL boundaries, causing daily congestion around perimeter streets like Lungotevere and Via Gregorio VII.

Outside the core, the city's vast metropolitan area is structured around the Grande Raccordo Anulare (GRA), a 68-kilometer ring motorway that encircles Rome. The

[49] Fondazione per lo Sviluppo Sostenibile. (October 23, 2023). Provincial capitals with the largest number of shared e-scooters in operation in Italy in 2022 [Graph]. In Statista. Retrieved April 26, 2025, from https://www.statista.com/statistics/1462424/e-scooter-sharing-vehicles-italy-by-city/

[50] Roma Sito Turistico Ufficiale

[51] INRIX. (March 9, 2020). Cities with the longest traffic jam delays in Europe in 2019, based on average number of hours lost per year [Graph]. In Statista. Retrieved April 26, 2025, from https://www.statista.com/statistics/1112832/cities-hours-lost-traffic-jams-europe/

GRA, together with the city's radial highway system, absorbs massive volumes of daily commuter traffic. It is not unusual for major junctions, such as those connecting with the A24 (east), A1 (north and south), Via Aurelia (west), and Via Pontina (south), to experience severe slowdowns during both morning and evening peaks.

The GRA's critical role in regional commuting means that even minor disruptions quickly escalate into multi-kilometer tailbacks. For instance, the A24 approach from the eastern suburbs regularly sees queues stretching for kilometers during the morning rush hour. Similarly, the Via Pontina corridor, serving a dense suburban population south of the city, suffers daily congestion where it intersects the GRA and beyond.

Inside the ring road, certain radial and semi-ring urban highways, the so-called *tangenziali*, face similar issues. The Tangenziale Est, for example, funnels enormous volumes of traffic across the city's northeastern quadrant and is notorious for gridlock, particularly near Tiburtina Station and San Lorenzo. Other major corridors like Via Cristoforo Colombo, Via Salaria, and Via Appia Nuova also experience relentless stop-and-go traffic for much of the day.

In short, congestion in Rome is a geographically widespread phenomenon. It radiates outward from the historic center, gripping not only the core but also the beltways and highways leading into and out of the city. The combination of an urban form ill-suited to mass motorization, a sprawling metropolitan footprint, and a strong car culture results in a multi-nodal congestion pattern that severely hampers urban mobility across the entire metropolitan area.

4.2.2 Temporal Patterns of Congestion

Rome's congestion levels follow a distinct rhythm throughout the day, the week, and the year, but it's far from a simple pattern. The city's traffic pulses with daily life, shaped by commuting habits, tourism, work schedules, and the seasons.

On weekdays, the morning rush begins early, peaking between 7:30 and 9:30 a.m., as huge numbers of commuters pour in from the suburbs and outer districts. These two hours alone account for about 20% of daily trips, showing just how compressed and intense the city's mobility demand can be. During this window, traffic on the main corridors slows dramatically, and the main inbound arteries often stretch into kilometers of stop-and-go movement.

The evening rush unfolds differently. Starting around 5:00 p.m. and stretching until well past 8:00 p.m., outbound traffic gradually builds. Part of this extended evening peak reflects Rome's cultural rhythms: many people finish work later, run errands, or participate in social activities before heading home. Although the morning and evening peaks are roughly similar in volume, the evening congestion tends to last longer.

Midday traffic, between the two rushes, never truly dies down. Around 1:00–2:00 p.m., there's a noticeable uptick linked to lunch breaks, errands, and deliveries. In a city like Rome, where tourism is strong and many businesses keep traditional hours, traffic remains substantial throughout the day, particularly around the city center and commercial areas.

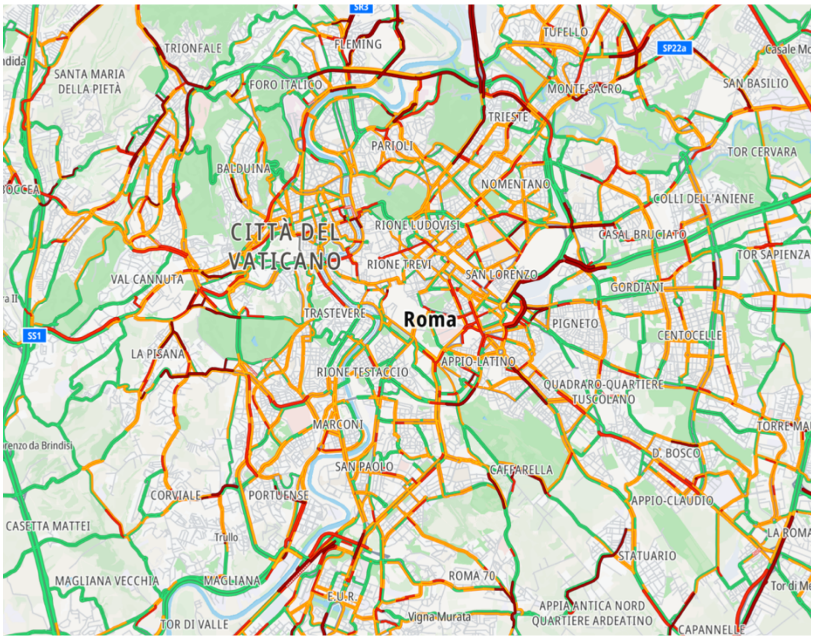


Figure 11. Rome traffic congestion on a Wednesday at 6pm. It is clear how the city center suffers major delays, while key arteries from and to the city (Via Tiburtina, Nomentana, Salaria) are particularly clogged. Source: [TomTom Rome Real Time Traffic Report]

Tourism adds another layer of congestion, especially around famous sites like the Vatican, Piazza Venezia, or the Colosseum. Even late in the morning or mid-afternoon, hours that in many cities are quieter, Rome can still feel saturated, thanks to fleets of tour buses, taxis, and rental cars navigating the historic streets. The weekly cycle also leaves a clear imprint. Tuesdays through Thursdays are generally the worst days for traffic, as the workweek hits full stride. Mondays tend to be a little lighter, while Fridays often see earlier congestion in the afternoon, as residents head out of town for the weekend, a ritual that clogs the GRA ring road and the primary radials leading out of the city.

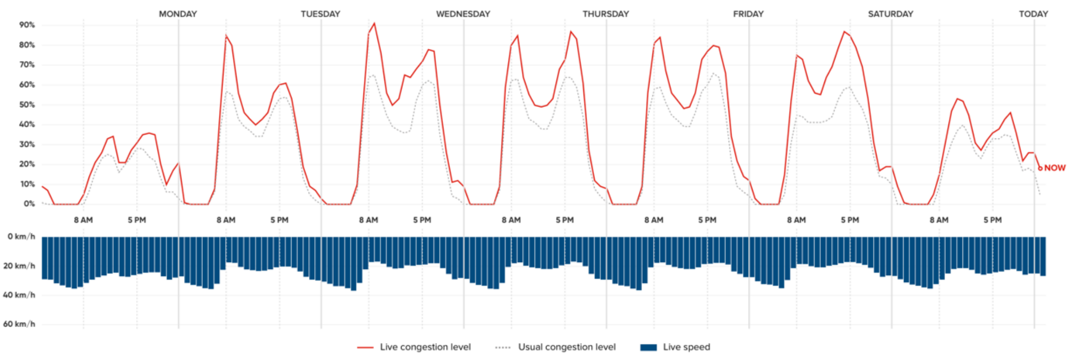


Figure 12. Weekly congestion and average speed per hour in Rome. Source: [TomTom Rome Traffic Index]

On weekends, the profile changes. Saturday afternoons are often jammed near shopping malls and nightlife districts, and while Sundays are quieter overall, special events like football matches, open museums, or large religious ceremonies can cause sudden local bottlenecks. Even when events are absent, Rome's strong car culture keeps weekend traffic far from negligible.

Seasonal shifts are just as significant. During the traditional holiday exodus in August, Rome empties out and traffic drops dramatically. Typically, gridlocked streets move freely, offering a rare glimpse of a less congested city. Yet in recent years, rising summer tourism has kept the center busier than it once was. September brings an abrupt return to heavy traffic, as schools reopen and offices resume normal operations. Traffic reports regularly highlight the *rientro*, the mass return in the city, as one of the most stressful periods for Roman drivers. Other months like October and November also tend to be heavy, while December brings congestion surges around Christmas shopping periods.

Weather, accidents, and roadworks often act as wildcards. A sudden rainstorm or a major crash on the GRA can instantly turn a manageable commute into a two-hour ordeal, and the worrying numbers of car crashes and fatal accidents, respectively 13,000 and 116 in 2023, making the Italian Capital 6th in the world in this discouraging ranking, contribute to worsening this already complex landscape[52]. Rome's aging infrastructure, including frequent maintenance and long-term metro construction projects, compounds these challenges.

4.2.3 Recent Urban Mobility Policies and Their Impacts

Over the past few years, Rome has introduced a series of urban mobility policies, aiming to reshape how people move through the city. These initiatives range from expanding traffic-restricted areas to updating the public transport system and managing the explosion of micro-mobility services like e-scooters. While each measure targets a specific aspect of the problem, together they form the city's broader attempt to tackle congestion and encourage more sustainable transport choices.

Rome's system of ZTL has been a fixture in the historic center for decades, but recent years have seen a tightening and expansion of these restrictions. By 2022, the city had restored pre-pandemic ZTL hours, after suspensions during COVID, and even started discussing further extensions to the night-time ZTLs in nightlife districts like Trastevere and San Lorenzo.

In parallel, the city moved toward a broader low-emission zone (ZBE) model. The Fascia Verde, a wide green belt around the city's core, now bans older, more

[52] ITF. (5. November, 2020). Durchschnittliche Anzahl der Todesfälle im Straßenverkehr weltweit in ausgewählten Städten 2018¹ (Todesfälle je 100.000 Einwohner) [Graph]. In Statista. Zugriff am 26. April 2025, von https://de.statista.com/statistik/daten/studie/1207893/umfrage/todesfaelle-im-strassenverkehr-weltweit-nach-stadt/

polluting diesel vehicles during the day. The idea is not just to limit traffic in the center, but to gradually push cleaner vehicles citywide.

The impact on congestion has been uneven. Within the central ZTLs, traffic volumes have clearly dropped, fewer cars are entering the city's heart during restricted hours, and public transport performance (especially buses) has improved slightly on key streets like Via del Corso. Air quality data also show small but measurable improvements inside the ZTL.

Yet outside the restricted zones, traffic hasn't necessarily disappeared; it has shifted. Streets like Lungotevere and Via Gregorio VII, just beyond the ZTL boundaries, often see heavier flows when restrictions are active. Residents in these areas have voiced concerns about "spillover traffic," highlighting a common challenge: localized traffic bans can displace congestion without reducing it overall.

As for the broader LEZ, its full impact remains to be seen. While some residents have upgraded their vehicles or switched to alternatives, there has been pushback too, protests in late 2023 pointed to fears about affordability and access. In practice, if the LEZ gradually cuts the number of old cars on the road without simply encouraging mass vehicle replacement, it could contribute to cleaner air and eventually to lower congestion levels. But for now, the effect on traffic volumes seems modest.

Rome’s Metro Line C project, the first new subway line in decades, has been slow-moving but symbolically important. Since its extension to San Giovanni station in 2018, Line C has offered a new east-west connection across peripheral neighborhoods traditionally underserved by rail.

Work continues to push the line deeper into the center, with the eagerly awaited Colosseo/Fori Imperiali station scheduled to open in 2025. This extension is critical: linking Metro C to the existing Lines A and B should vastly improve network connectivity, making public transport a more attractive alternative to driving for many residents and tourists.

Each new station brings incremental gains. Though the scale was modest, the San Giovanni extension already encouraged some residents in areas like Pigneto and Centocelle to shift away from car use. The impact could be more visible once Colosseo opens, giving tourists and locals a direct metro link to one of Rome’s biggest attractions.

Beyond the metro, Rome has also invested in new buses (including electric models), expanded bus lanes, and started planning new tramlines. Some corridors, like Via Tiburtina and Via Nomentana, have seen travel time improvements for buses, helping public transport’s competitiveness. However, service reliability issues, including vehicle breakdowns and sporadic strikes, continue to plague the system and limit its overall impact on reducing car dependency.

Construction itself has not been without consequences. Major worksites, especially near historic areas like Piazza Venezia and Fori Imperiali, have disrupted road networks, creating local bottlenecks and detours. Although these disruptions are temporary, they have added another layer of complexity to Rome's already strained mobility system.

Overall, transit improvements are slowly nudging Rome toward better alternatives to driving, but the pace is gradual. The real benefits will likely emerge in the second half of the 2020s, if, and only if, investments stay on track and service reliability improves.

4.2.4 Expert Opinions and Future Projections

Among transport engineers, urban planners, and mobility researchers, there's broad agreement on two points: first, that Rome's traffic congestion is a deeply rooted, complex issue; and second, that real improvement is possible, but only with sustained, large-scale interventions.

Technical experts often describe Rome's network as structurally vulnerable to bottlenecks. The city's historical layout, with limited bridge crossings over the Tiber and a relatively sparse metro system compared to other European capitals, naturally funnels large volumes of traffic into a few critical corridors. Looking ahead, the city's official mobility plans are cautiously optimistic. If all the measures currently planned are completed, namely the full opening of Metro Line C into the city center, expansion of tram lines, stricter low-emission zones, and widespread traffic calming measures, the modal share of private vehicles could drop from about 59% today to around 50% by 2030. Under that scenario, average congestion delays could fall by 15–20%, a significant but hardly revolutionary improvement. However, the alternative scenarios that experts warn about are sobering. If car ownership continues to rise, if remote work trends reverse, or if planned public transport projects are delayed (as often happens), then congestion could worsen beyond pre-pandemic levels. Some projections suggest that daily vehicle kilometers traveled in Rome could grow by about 5% between 2019 and 2025 if no further action is taken[53].

The Jubilee Year of 2025 adds another layer of complexity. Rome is currently welcoming millions of extra visitors during the event, placing enormous pressure on its transport systems. City planners are scrambling to accelerate infrastructure upgrades and temporary traffic management measures to avoid complete gridlock during peak pilgrimage periods. Experts widely view the Jubilee as a critical stress test: if Rome's mobility system can handle 2025 without collapsing into chaos, it would bode well for longer-term resilience.

Regarding emerging strategies, many specialists advocate for a mix of supply- and demand-side measures. On the one hand, expanding public transport and micro-mobility infrastructure remains essential. Conversely, tools like congestion pricing, stricter parking controls, and incentives for remote working could help shift behavior

[53] Carrese S, Cipriani E, Colombaroni C, Crisalli U, Fusco G, Gemma A, Isaenko N, Mannini L, Petrelli M, Busillo V, Saracchi S. Analysis and monitoring of post-COVID mobility demand in Rome resulting from the adoption of sustainable mobility measures. Transp Policy (Oxf). 2021 Sep;111:197-215. doi: 10.1016/j.tranpol.2021.07.017. Epub 2021 Jul 22. PMID: 36568353; PMCID: PMC9759737.

more decisively. London's congestion charge is frequently cited as an example Rome could eventually follow, although politically, introducing a similar scheme in Rome would be far from easy.

There's also growing interest in technological solutions, like smart traffic lights and real-time traffic management platforms. While helpful, these are generally seen as marginal gains rather than game-changers: no amount of algorithmic optimization can solve the fundamental imbalance between too many cars and too little road space[54].

Ultimately, the consensus among experts is that Rome is at a crossroads. The foundations for change are being laid, but whether the city truly transforms its mobility system will depend not only on infrastructure investments but on political will and cultural shifts. Without a genuine reduction in private car dependency, congestion will likely remain a defining feature of daily life in the Eternal City.

Given the complexity of Rome's traffic, shaped by a mix of private cars, scooters, buses, tourists, and unpredictable local behaviors, traditional modeling approaches often fall short. This is where ABM becomes especially valuable. Capturing everything from commuters adjusting their routes to avoid a ZTL, to tourists randomly circling for parking near the Vatican, to delivery drivers double-parking in a second lane on a narrow street, trying to reflect the "messiness" of real-world behavior, is a really complex and articulated task. But at the same time, this opens enormous potential for algorithmic optimization.

5. Analysis of the Results

For each of the two cities, the code helps answer three main research questions:

1. What is the most efficient mode of transportation under ideal conditions, where vehicles travel at the speed limit and congestion is absent, and can this be further optimized?

2. In a day-trip scenario, which mode offers the best travel solution, considering slower movement and planned stops?

3. Under congested rush hour conditions, would individuals be better off if they behaved rationally, switching modes to avoid traffic bottlenecks as the model allows?

Comparisons and analyses will be conducted considering the total distance travelled, in meters, by each mode of transportation in the same period, measured in 1000 `ticks`. TomTom Traffic Report Index data will be employed in the congestion scenarios, tracking the location of the most congested spots identified in Figures 5

[54] Engineering Rome 2026

and 7. Geneva traffic data show the average speed in the city center to be 18.8 km/h during the morning rush hour and 17.9 km/h during the evening rush hour[55]. In Rome, these figures become 17.1 km/h and 16.6 km/h, respectively[56]. The move-agent functions previously defined will be modified, adding congestion factors, setting the speed of travel according to the average speed measures discussed above, to faithfully reproduce congestion conditions. To introduce full rationality by agents, cars that have to travel through highly congested spots, with an attention radius of 0.5 degrees, incorporating also adjacent nodes, will be allowed to switch mode of transport to reach their destinations: 90% of them will continue their trip walking, while the remaining will ride a bike to their destinations, in order to adopt the same split in mode of transport defined in Chapter 4.

5.1 Geneva Results

Under ideal traffic conditions, and considering 50 agents for each transport mode, the total distance travelled in meters in 1000 ticks is as follows:

Ideal Conditions	Cars	Pedestrians	Bikers
Total Distance (by Category)	138.040,14	46.210,63	103.940,61
Total Distance (per Agent)	2.760	924	2.088

Table 5. Geneva Travelled Distances in Ideal Traffic Conditions.

As expected, car agents are the ones travelling the most distance in the same period of time. However, the influence of traffic lights and road exclusivity is already visible, as bikers advanced only 24.4% fewer meters than cars. The difference in road structure and congestion will be much more evident in the analysis of rush hours. Regardless of parking availability and its price (2.80 CHF/hour in Geneva), private transportation methods, such as cars and motorbikes, still represent the most efficient solution under ideal traffic conditions, with smooth traveling and no congestion.

In the day-trip scenario, results discourage private car usage even more.

Day-Trip Scenario	Cars	Pedestrians	Bikers
Total Distance (by Category)	84.843,5	44.146,3	79.442
Total Distance (per Agent)	1.696	882	1.588

Table 6. Geneva Travelled Distances under the Day-Trip Scenario.

[55] TomTom Geneva Traffic Index Report
[56] TomTom Rome Traffic Index Report

Considering the relatively small extension of Geneva and the closeness of points of interest in the city, using a car represents the least efficient possible means of transportation for a day trip, with only 6% more distance travelled than bikes and less than double compared to walking. This is due to pedestrian-exclusive streets in the city center, which force car users to park further away from the desired destination and then proceed on foot, reducing the amount of meters recorded by the function. And being realistic, passing by the lake or taking pictures at St. Pierre Cathedral while riding a bike or having a peaceful stroll sounds much more scenic than just driving from one point to another. It is also interesting to see how the ratio between the distance travelled walking and by bike decreases during a day-trip, from 45% to 55%. This is due to the fact that sightseeing allows pedestrians to keep their usual walking pace, while bikers slow down and peacefully enjoy their ride.

During morning rush hours, the congestion level is clearly visible: in the same amount of time, cars manage to travel 12% less distance than pedestrians, as they are allowed to also take public transport, knowing that tram lines don’t share roads with cars and therefore don’t experience the same level of traffic. It is evident that in these conditions, bikes are the preferred options: an extensive bicycle lanes network and the favorable topography of the city, with few uphill or downhill slopes, make cycling both convenient and efficient, allowing bike commuters to travel 19% and 35% more distance than pedestrians and car drivers, respectively.

Morning Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	52187.7	59198.2	70408.8
Total Distance (per Agent)	1043.7	1183.4	1408

Table 7. Geneva Travelled Distances in the Morning Rush-Hour.

After allowing for mode switching, the figures look slightly better for car drivers.

Morning Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	61040	48824.5	71287
Total Distance (per Agent)	1220.8	998.5	1443.7

Table 8. Geneva Travelled Distances in the Morning Rush-Hour after allowing mode-switch.

Cycling is still confirmed as the best commuting option, travelling 16% more distance than mixed-mode agents. It is however interesting to see pedestrians walk 11% less distance compared to the normal morning congestion setting. This is likely due to increased crowding on public transport lines. In the model, after mode switching, the number of pedestrians nearly doubles, which also increases the number of people using public transport, leading to longer waiting times as buses become overcrowded. Faced with the prospect of a stressful journey packed like sardines, many may prefer to wait for the next available vehicle instead of boarding immediately.

The same phenomenon can be seen in the evening rush hour setting, exacerbating the difference in travelling distance between bikes and other modes of transport.

Evening Rush-Hour	**Cars**	**Pedestrians**	**Bikers**
Total Distance (by Category)	49776	52818.2	70621.3
Total Distance (per Agent)	995.3	1056.4	1412.4

Table 9. Geneva Travelled Distances in the Evening Rush-Hour.

Allowing mode switch decreases the bikes/cars deviation from 45% to 33% more distance travelled in favor of the former, while pedestrians share the same conditions as the morning scenario previously outlined.

Evening Rush-Hour	**Cars**	**Pedestrians**	**Bikers**
Total Distance (by Category)	58742	49637.4	78562
Total Distance (per Agent)	1174.8	992.7	1573

Table 10. Geneva Travelled Distances in the Evening Rush-Hour after allowing mode-switch.

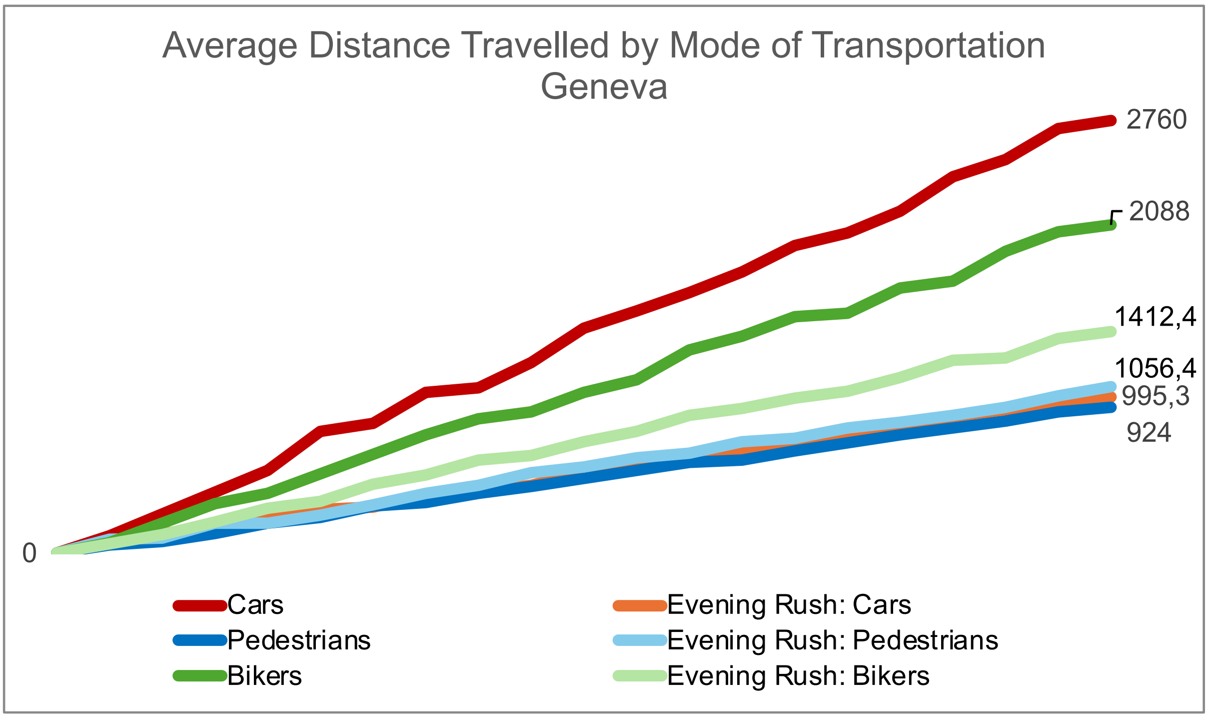


Figure 13. Average Distance Travelled by Mode of Transportation – Geneva.
The difference in travelled distance by cars in Ideal conditions vs. Evening Rush Hours is clearly visible, especially if compared to bikes, which do not experience such a variation.

Figure 13 pictures the average distance travelled by agents of all categories. The main take-away is the striking difference between the journey lengths of drivers under normal traffic conditions and evening rush-hour, especially compared to the other modes of transport. Pedestrians, unsurprisingly, are the category retaining the most distance under the two scenarios. Bikes remain the most efficient mode of transport in rush hour conditions, as shown by the considerable gap with the distance travelled by cars.

5.2 Rome Results

The first results from Rome network's simulation highlight some particular differences with respect to the Geneva one:

Ideal Conditions	Cars	Pedestrians	Bikers
Total Distance (by Category)	39.501,15	27.049,24	28.911,88
Total Distance (per Agent)	790	541	578,2

Table 11. Rome Travelled Distances in Ideal Traffic Conditions.

The first overall difference is that distances are 59% lower, on average, than those recorded in the Geneva simulation, underscoring the already covered network disparities in terms of road composition. The biggest gaps can be seen confronting the cars and bikes simulations, respectively 72% and 87% lower than the previous reproductions. Before delving into further analyses, these results already carry an important message: Rome, as a city, is not an efficient playground for private means of transport.

Day-Trip Scenario	Cars	Pedestrians	Bikers
Total Distance (by Category)	33.325,25	28.451,76	35.815,65
Total Distance (per Agent)	667	589	716,3

Table 12. Rome Travelled Distances under Day-Trip Scenario.

In the day-trip scenario, the limitation of private car usage in Rome historical city centre really become visible. While walking distances remain flat, with a 10% tolerance level, bikes confirm themselves are the preferred method to enjoy a peaceful ride while sightseeing and exploring the Capital's beauties, allowing higher travel distance than cars. Unexpectedly, in these conditions bikes travel more distance than in the ideal scenario previously analyzed; the cause can be attributed to the reduced concentration of cars in the city center, which effectively frees up road space, providing cyclists with safer and more favorable riding conditions. On the other hand, cars travel 18% less distance than before: without taking into account the real-world propensity of Roman drivers to resort to illegal parking practices and to risk fines, behaviors inherently difficult to quantify and incorporate accurately within the parameters of a basic simulation model, this reduction still feels reliable. Even those drivers that want to test the limit of Rome’s police officers’ patience will realistically give up on their cars and go on walking.

Moving to rush hours analyses, the figures totally discourage cars’ usage.

Morning Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	25.549,5	26.232,7	36.121,2
Total Distance (per Agent)	577	537	822

Table 13. Rome Travelled Distances in the Morning Rush-Hour.

During the morning rush hour, the average distance traveled by cars per agent decreases by 27%, resulting in only a marginal 7% advantage over walking. In this scenario, bicycles emerge as the most efficient mode of transportation, traveling 53% further than pedestrians and 47% further than drivers.

Morning Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	28.848,3	26.863,39	41.104,33
Total Distance (per Agent)	697	538	749

Table 14. Rome Travelled Distances in the Morning Rush-Hour after allowing mode-switch.

After enabling mode switching, allowing drivers to opt for public transport or walking, the morning scenario shows modest improvement: car commuters now travel 20% further than previously, while the distances traveled by pedestrians and bikers remain stable, with variations below a 10% threshold.

Evening Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	34.863,7	26.906,11	37.471,38
Total Distance (per Agent)	511	525	722

Table 15. Rome Travelled Distances in the Evening Rush-Hour.

During evening rush hours, cars become the least efficient transport mode, consistent with the congested traffic conditions highlighted in Section 4. Indeed, anyone who has driven in Rome between 6 p.m. and 8 p.m. has likely experienced severe congestion, reconsidering their car usage. In this period, pedestrians cover approximately 3% more distance than car commuters. However, pedestrians are not immune to the consequences of congestion either, given their heavy reliance on public transportation: they travel, on average, 4% less compared to ideal traffic scenarios.

Evening Rush-Hour	Cars	Pedestrians	Bikers
Total Distance (by Category)	26.985,3	26.315,7	34.233,8
Total Distance (per Agent)	539.7	526	684.6

Table 16. Rome Travelled Distances in the Evening Rush-Hour after allowing mode-switch.

When mode switching is permitted in the evening, car users slightly increase their traveled distance by 5%, thus surpassing pedestrians, whose distances remain unchanged. Interestingly, cyclists reduce their traveled distance by 6% after drivers are allowed to switch to walking or cycling. A plausible explanation for this unexpected decline is that the influx of former car commuters onto bike lanes, often inadequately sized or poorly structured in Rome, and non-existent in the city center, may generate additional congestion on cycling paths, thereby slowing down overall cycling traffic.

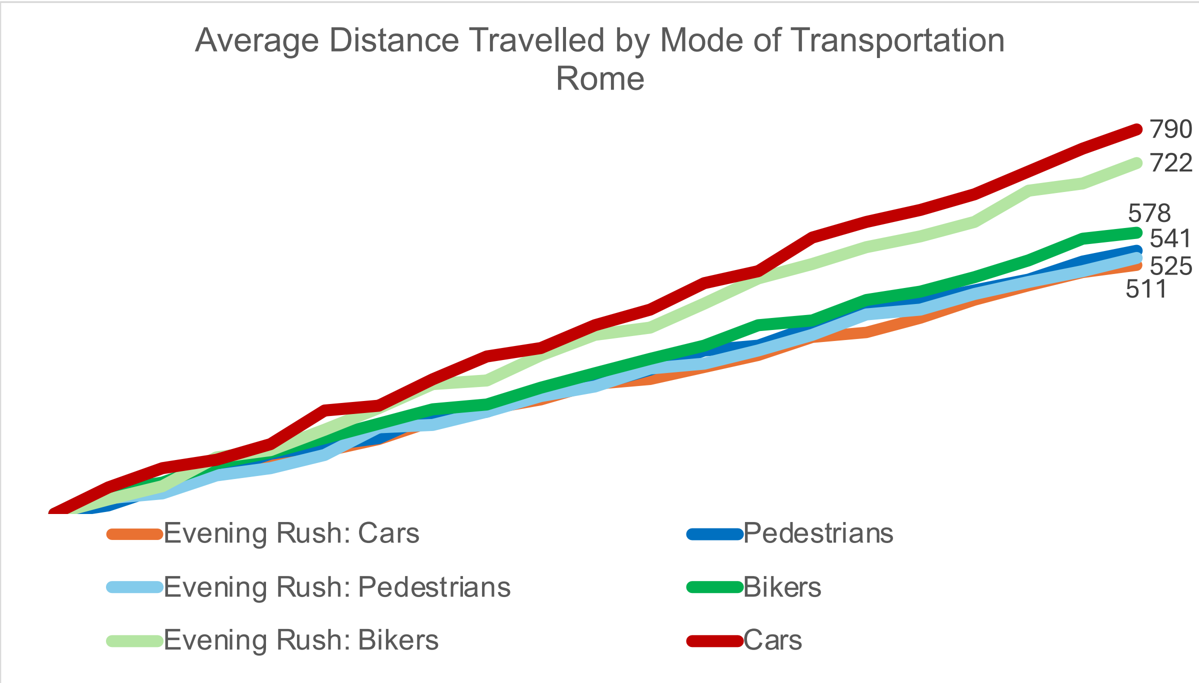


Figure 14. Average Distance Travelled by Mode of Transportation – Rome.
Striking gap between distance travelled by cars in Ideal conditions vs. Evening Rush Hours.

Figure 14 highlights the complex traffic conditions in Rome for all categories of agents. Cars, in particular, become the worst mode of transport during the evening rush hour, covering less distance than pedestrians. Bikes remain the most efficient mode of transport, especially during rush hours.

Comparing these results with the actual travel data provided by TomTom, it is possible to analyze discrepancies and variations that the simulation couldn't capture. In the simulation, time was represented by ticks, with agents traversing an average of 132 edges over a 1000-tick interval in Rome and 69 in Geneva. To evaluate the realism of this behavior, 1000 samples of actual paths, each consisting of exactly 132 road segments, were extracted from the TomTom dataset. By summing the real-world distances and observing the actual average speed of travel of these samples, it was possible to estimate how accurately the simulation replicates observed mobility patterns. TomTom Data trials results, observable in Figure 15, suggest car drivers in Rome travel, on average, just 2,36 meters more than the simulation results (790 meters, Table 11). The mean of the actual speeds derived from the sampled TomTom data is notably lower than the average speeds reported during morning and evening rush hours in the TomTom Traffic Index.

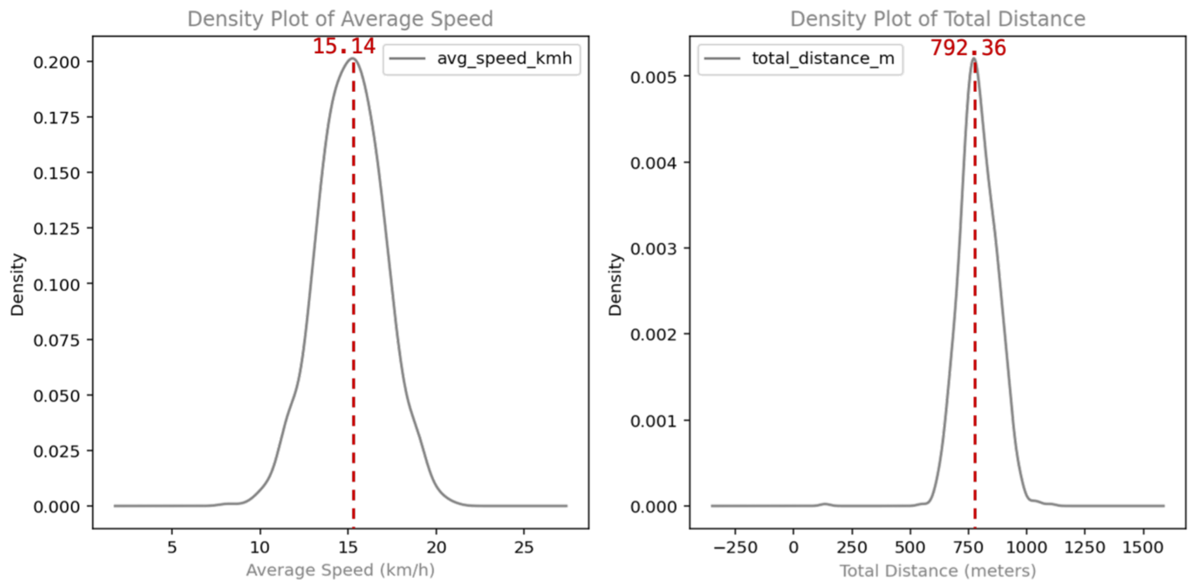


Figure 15. Density plots of Average Speed and Total Distance travelled across 132 edges from a 1000 observations sample from Rome TomTom Data.

This discrepancy can be partly attributed to the nature of the dataset: the free trial version covers only a subset of the total road network in Rome and reflects conditions during a specific time window. Nonetheless, the result is noteworthy. It suggests that even over short paths, subtle behavioral and environmental factors, such as brief traffic build-ups or irregular parking, can accumulate and significantly slow down travel, highlighting dynamics that may not be fully captured in broader traffic averages and indicators. To simulate more realistic driving behavior, the agent speed on each road segment is computed as a function of the posted speed limit and a scenario-specific modifier, $v_{sim} = (v_{limit}/50) \cdot f$.

This approach introduces a dynamic tolerance mechanism, allowing for relatively higher speeds on roads with higher speed limits, reflecting the common tendency of drivers to exceed limits on wider or faster roads. On highways or arterial roads with higher v_{limit}, like some portions of the Grande Raccordo Anulare in Rome with speed limits of 130 km/h, this results in a multiplier effect, allowing agents to exceed the legal limit slightly. Conversely, it imposes a proportionally greater penalty in areas with lower speed limits, such as narrower residential streets, where speeding is less common or more constrained by road conditions. The discount factor was designed to simulate minor disruptions in otherwise smooth traffic flow, as previously discussed. By slightly reducing the effective speed, it accounts for small, often unobservable interruptions, such as brief stops, hesitations at intersections, or mild congestion, that typically occur even under relatively fluid driving conditions.

Geneva presents a slightly different scenario. A more robust infrastructure, a limited number of fully residential areas and easier overall navigability result in longer edges, averaging 47 meters, compared to Rome's average length of 17 meters. Drivers, in the simulation, travelled over 69 edges in the 1000-tick interval, with an average of 2670 meters (Table 5). Actual path samples drawn from the TomTom data, shown in Figure 16, suggest a lower real-world average of around 1.950 meters. This 29% discrepancy is significant and offers a compelling insight. It may be partially explained by the nature of the dataset, which shares the same temporal and spatial constraints discussed earlier in the context of Rome, but there is a structural factor worth noting. As outlined in Chapter 2.1, only 3% of Rome's network nodes are traffic lights, 1457 out of 43657, compared to 26% in Geneva 280 out of 1076. The presence of traffic lights, excluded as variable for the model because of the additional computational performances required and the absence of exact data regarding their spatial localization, seems to have an impact on the error of the model against normal traffic conditions.

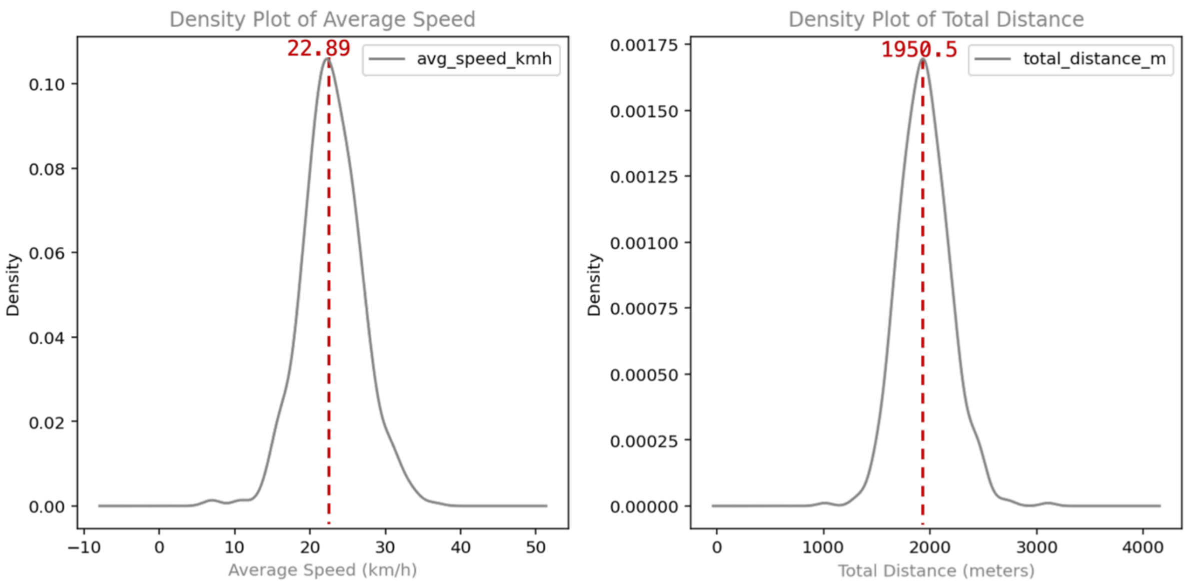


Figure 16. Density plots of Average Speed and Total Distance travelled across 69 edges from a 1000 observations sample from Geneva TomTom Data.

6. Conclusion

The comparative analysis of Geneva and Rome illustrates how urban structure, transportation policy, and cultural practices critically shape urban mobility outcomes. Geneva's compact geography, bounded by natural constraints such as Lake Geneva and the Rhône River, inherently channels traffic into a limited number of corridors, causing persistent congestion on key arteries like the Pont du Mont-Blanc. Nevertheless, its dense, pedestrian-oriented urban fabric and proactive policy measures, particularly the rapid expansion of dedicated cycling infrastructure and protected cycle tracks, significantly enhance sustainable transportation options. Simulation results confirm bicycles as the most efficient mode during peak hours, effectively navigating congestion bottlenecks and demonstrating the benefits of Geneva's strategic investments in active mobility.

Rome's sprawling metropolitan layout, historical urban constraints, and pronounced car-centric culture exacerbate its chronic congestion issues. The city's high motorization rate, coupled with fragmented and outdated public transport infrastructure, continually reinforce dependence on private vehicles. Despite recent policy interventions like the expanded aiming to reduce vehicular traffic, these measures often shift congestion rather than eliminate it, highlighting enforcement challenges and cultural resistance. The simulations mirrored this reality effectively, particularly during evening rush hours, where pedestrians notably outperformed cars due to severe congestion, reflecting real-world observations like frequent traffic delays along the Lungotevere and key radial routes such as Via Tiburtina and Via Appia Nuova.

An important insight from the model is the discrepancy between idealized rational behaviors simulated in the ABM and complex, unpredictable real-world behaviors, including Rome's common illegal parking practices and inconsistent adherence to traffic regulations. This emphasizes the model's limitations and highlights the need for improved data inputs and more nuanced behavioral modeling backed by increased computational power, to accurately capture the granularity of human decision-making complexities in urban mobility.

Explicitly addressing the research questions from Section 5:

- Under ideal conditions, private vehicles remain the most efficient mode due to uninterrupted flow and higher travel speeds. However, this efficiency quickly diminishes under realistic congestion scenarios.

- In a day-trip scenario, bicycles prove to be the most effective and enjoyable mode of transportation, especially in Geneva, where pedestrian-oriented urban spaces enhance cycling convenience. Rome shows similar trends, although cycling advantages are more evident in the reduced presence of cars, particularly in the historical city center.

- Under congested rush hour conditions, rational mode-switching behavior significantly improves individual travel efficiency. In both Geneva and Rome, allowing drivers to shift to walking or cycling substantially alleviates congestion impacts, although this effect is more pronounced in Geneva due to its superior cycling infrastructure.

	Cars Rome	**Cars** Geneva	**Pedestrians** Rome	**Pedestrians** Geneva	**Bikers** Rome	**Bikers** Geneva
Ideal Conditions	790	2.760	541	924	578,2	2.088
Day-Trip Scenario	667	1.696	589	882	716,3	1.588
Morning Rush	577	1.043,7	537	1.183,4	822	1.408
Morning Rush mode switch ON	697	1.220,8	538	998,5	749	1.443,7
Evening Rush	511	995,3	525	1.056,4	722	1.412,4
Evening Rush mode switch ON	539,7	1.174,8	526	992,7	684,6	1.573

Table 17. Comparison of all simulation results analytics.

The simulation results reveal clear differences in mobility efficiency between Rome and Geneva, highlighting how urban structure and infrastructure shape travel behavior. In every scenario, agents in Geneva consistently covered more distance per trip than those in Rome, particularly when traveling by car. Under ideal conditions, cars in Geneva averaged 350% the distance travelled in Rome; in all other scenario, Swiss drivers accumulate at least 80% more meters than Italian ones. Pedestrians and bikers also performed better in Geneva, where walking agents regularly traveled nearly twice as far as their Roman counterparts, and biking distances were up to three times higher in some cases. These results reflect Geneva's compact layout, well-integrated transport systems, and prioritization of sustainable mobility. In contrast, Rome's congested, car-dependent network and fragmented infrastructure impose constraints across all travel modes, especially during peak hours. This gap illustrates the real-world implications of urban design, with Geneva enabling smoother, longer, and more efficient travel for all types of agents. The model reproduced reliably the distances travelled by drivers in Rome during normal traffic conditions, while, in Geneva, it overestimated their paths. This punctuates the huge potential developments of projects in this field, from more precise and tailored analytics, like Geneva's significantly higher density of traffic lights, in this case, to higher computational power and resources. Imagining full availability of data, further steps would include introducing more personalized traits and parameters for agents for higher granularity and variation between behaviors; simulating the flow of traffic hour-by-hour, taking into consideration the smallest temporal patterns; incorporate real-time traffic indicators coverage for hands-on policy testing and intervention.

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