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MASTER'S THESIS IN SAFETY ENGINEERING FOR TRANSPORT, LOGISTICS AND PRODUCTION

Modeling and simulation of an urban Car Pooling service: the case study of Genoa

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Abstract

This thesis presents a discrete event simulation model of an urban carpooling system for the city of Genoa, utilizing real-world data to simulate interactions between drivers and riders based on actual travel times throughout the city's road network. The model focuses on the dynamics of pairing drivers with riders, including the processes of picking up and dropping off at designated network points.

Operational through a dynamic matching system, the model coordinates driver-rider pairings according to their respective routes and schedules, taking into account the urban traffic conditions. It incorporates crucial parameters such as travel time variability, individual start times, and specific route links for pick-up and drop-off activities, offering a detailed picture of urban transport scenarios.

The simulation provides insights into the operational aspects of a carpooling system within a metropolitan setting, exploring its feasibility and operational dynamics. This study highlights the role of precise data and thorough modeling in enhancing urban transportation solutions through carpooling.

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Contents

1 Introduction

1.1 Background

In the pursuit of sustainable urban development, shared mobility emerges as a transformative approach, reshaping our interactions with urban environments and transportation systems. In recent years, urban mobility has experienced a paradigm shift driven by significant advancements in technology and changing societal behaviors. This transformation is profoundly influenced by the concept of shared mobility, which integrates the use of technology-enabled platforms to facilitate shared access to transportation modes such as cars, bicycles, and E-Scooters. The transition towards shared mobility is not merely a response to technological innovation but also a strategic approach to address urban congestion, environmental concerns, and the efficient use of urban spaces.

The stability of traditional transportation has been challenged by a surge in the sharing economy, with shared mobility at its core. Services like ride-sharing, car-sharing, and micro-mobility solutions such as shared E-Scooters and bikes have begun to redefine the landscape of urban transportation. These modalities offer potential benefits including reduced vehicle ownership, lower greenhouse emissions, and the democratization of transportation access [30]. The relevance of shared mobility extends beyond convenience, positioning itself as a critical component in the quest for sustainable urban development.

The technological framework that supports shared mobility is pivotal. Innovations such as mobile connectivity, big data analytics, and autonomous vehicle technology are essential to the efficacy and expansion of shared mobility services. These technologies not only facilitate the operational aspects of shared mobility but also enhance user experiences and increase the adoption rates of these services.

The environmental impact of shared mobility is profound. By potentially reducing the number of privately owned vehicles, shared mobility can decrease urban congestion and lower emissions per capita. However, the realization of these benefits is contingent upon supportive policy frameworks that promote the integration of shared mobility into existing urban transportation systems[6]. Policies need to be adaptive and forward-thinking to accommodate the rapid pace of technological change and the shifting patterns of urban mobility.

1.2 Research Objectives

This thesis explores the impacts of shared mobility on urban transportation systems, with a specific focus on enhancing sustainable urban mobility. The study will analyze the performance of a carpooling model in the city of Genova, concentrating on how effectively it operates within the broader urban transport framework. Through this approach, the thesis aims to contribute to a more comprehensive understanding of integrating shared mobility into urban transportation planning and sustainable development.

1.3 Thesis Structure

This thesis is structured to comprehensively examine the role of carpooling within shared mobility systems in urban environments, specifically focusing on its application in Italy.

- **Chapter 1: Introduction** - This chapter outlines the various objectives of the thesis and analyzes its structure.
- **Chapter 2: Theoretical Framework** - This chapter lays the foundational theoretical framework, introducing various shared mobility services and focusing on Italy's sharing mobility landscape. Particular emphasis is placed on carpooling, which is the central theme of this research.
- **Chapter 3: The Proposed Model** - This chapter of the thesis is about using Discrete Event Simulation (DES) to model carpooling systems. It covers the foundational principles of discrete event systems and their application in carpooling simulations, highlighted through flowcharts. The chapter also details the data collection methods, sources, and descriptions, and discusses the challenges and limitations faced in the simulation process.
- **Chapter 4: Case Study** - In this chapter, the construction of the simulation model is described in detail. The study area is described and this section elaborates on the model's inputs and outputs, as well as the parameters and variables that govern its functionality, providing a clear view of the operational mechanics behind the simulations.
- **Chapter 5: Results** - This chapter is devoted to analyzing the results obtained from the simulation model. This section interprets the data in the context of the study's objectives, offering insights into the effectiveness and implications of carpooling systems. This chapter includes also the conclusions of the thesis and the further developments

2 Theoretical Framework

2.1 Urban Development and Sharing Economy

2.1.1 Urban development

Cities, ranging from small agglomerations of fewer than 500,000 inhabitants to large metropolises with several million people, represent vital nerve centers necessary for the economic and social growth of any nation. The first 200 urban centers alone generate about 60% of the growth and job opportunities within OECD countries[28]. The interconnection of people, ideas, and knowledge allows a fairly stable core to self-sustain and grow by building an increasingly efficient network aimed at realizing common projects in all areas that structure the city. The role of cities will continue to grow in importance: currently, 55% of the world's population lives in urban centers, totaling 4.2 billion people out of 7.7 billion, and estimates suggest that by 2050, this percentage will reach around 68%[28].

The process of urbanization has shown impressive growth rates in the last century, with cities increasingly becoming hubs of attraction for people and commercial activities. Even the poorest countries have experienced significant migrations from rural areas to urban centers in search of better opportunities. This trend is expected to intensify notably: low-income and lower-middle-income countries (including almost all African countries, a large part of Asian countries, and some Latin American countries) are projected to increase their urban population from the current 32% and 40% to approximately 50% and 60% by 2050[28]. Urbanization is expected to continue growing in the coming decades even in high-income and upper-middle-income countries, although at a slower rate for the former group: currently, the urban population fraction averages around 80% in developed countries. This is one of the most critical themes in future urban development: urban agglomerations are expected to grow significantly, accommodating millions of people, so action must be taken now to make the city more usable. Cities are increasingly becoming global arenas and must face increasingly complex environmental, social, and economic challenges. They are responsible for about two-thirds of the energy consumed worldwide and approximately 70% of the globally emitted CO2. The OECD has estimated that urban pollution could cause between 6 and 9 million deaths annually by 2060[13]. Major metropolises are moving in this direction by creating an interconnected reality and embracing the digital age, which currently allows for the collection of vast amounts of data regarding people's behaviors and habits, the temporal use of commodities (energy, water, heating), citizens' mobility, etc. When used responsibly, this data represents a fundamental tool for addressing the challenges of a Smart city and optimizing all aspects.

2.1.2 Sharing Economy

The concept of the Sharing Economy encompasses a broader, more profound idea than merely lending or borrowing, it embodies the process of distributing one's possessions for others' use, and equally, receiving goods from others for one's personal use. This framework challenges the conventional wisdom around private ownership, juxtaposing it against traditional market transactions such as trading and gifting. Although frequently mistaken for these older economic interactions, sharing distinctly fosters synergies and promotes the conservation of resources, setting itself apart as a more collaborative and sustainable model.

The positive impacts of sharing practices are well-documented, particularly in services like carpooling and bike pooling. These models have shown considerable benefits, including significant reductions in individual stress levels and contributions to decreased environmental pollution. Such outcomes highlight the dual personal and communal advantages of adopting sharing-based models over more individualistic approaches inherent in traditional ownership and use of assets.

In recent years, the propensity for sharing among consumers has surged, with many viewing it as a viable and sustainable alternative to outright purchasing. This trend towards sharing is not just a contemporary shift but a re-emergence of ancient practices, albeit under the new guise of the modern Sharing Economy. This recent incarnation is a compelling and contemporary phenomenon that has attracted significant attention from both academic researchers and industry professionals, owing to its innovative approach to exploiting underutilized resources, which range from physical spaces to personal skills and competencies.

The Sharing Economy is often characterized by its economic model where the sharing of underutilized assets translates into monetary and non-monetary benefits for all parties involved. This model marks a departure from traditional economic interactions by prioritizing access over ownership. This paradigm shift is epitomized in the ”Access Economy,” which includes services such as carsharing and ridesharing. Here, consumers gain temporary access to physical goods that would otherwise remain idle, thus illustrating a significant transformation from the traditional norms of asset ownership.

While the Sharing Economy lacks a universally accepted definition, it is broadly understood to encompass various activities. These activities range from the recirculation of goods, exemplified by platforms like eBay and Craigslist, to the increased utilization of durable goods, as seen with Zipcar’s vehicle rental service. Additionally, the exchange of services through innovative platforms further illustrates the diverse applications of this economic model. This economic phenomenon is rapidly evolving, fueled by technological advancements and a shift in consumer ideologies towards prioritizing communal access over personal ownership. The shift from ”you are what you own” to ”you are what you share” encapsulates this transformation in consumer values, reflecting a deeper societal change towards more sustainable and community-oriented living.

The Sharing Economy leverages digital technology to facilitate efficient and effective use of resources. Platforms enable the easy sharing of not only goods but also information, services, and intellectual property. This has led to a democratization of access to resources, significantly altering how goods and services are consumed. The technology not only supports but actively enhances the connectivity between supply and demand, adapting dynamically to the needs of the user community.

2.2 Shared Mobility

Within the phenomenon of the sharing economy lies shared mobility, known as sharing mobility, which is a growing sector.

2.2.1 Mobility Models Compared (Individual/Shared)

Passenger travel can be conducted using various transportation modes, including rail, subway, streetcar, bus, ship, airplane, car, and motorcycle. The standardized measurement unit for categorizing mobility across these different modes is the passenger-kilometer (pkm), which represents the total number of passenger trips made using different modes of transport. Besides categorizing travel by the type of transportation system, it can also be classified by the ”intended use” or ”economic use” of the transportation means. Individuals can travel using private transportation methods, such as walking, cycling, motorcycling, or driving their own car, or they can opt for shared vehicle or trip options. The former is referred to as individual mobility, while the latter encompasses shared mobility services, including traditional public transport.

Individual mobility The widespread availability of high-performance cars, expanding road infrastructure, extensive fuel networks, and increased disposable income - among other significant factors - has led more and more people to own and use personal vehicles, especially automobiles. The growing population living and working in cities, coupled with the spread of activities across wider areas, known as urban sprawl, has further intensified the need for such travel. Today, in almost every country, social and spatial organization relies heavily on the widespread availability and regular use of automobiles (or other personal motor vehicles like motorcycles, scooters, and trucks for goods transport). Several practical aspects related to automobile use have made private cars increasingly desirable and necessary.

- **Accessibility**
  The dense road network allows direct connections between distant points. The fuel supply network makes the range of land travel virtually limitless, enabling any road-accessible location to be reached from another.

- **Availability**
  Unlike train travelers, motorists are not constrained by schedules. Those with a personal vehicle can travel directly from point A to point B without changing modes of transport and can do so at their convenience, stopping only when they choose.

- **Continuity**
  Private motorized mobility is characterized by uninterrupted travel. Owning a vehicle eliminates the need to buy tickets, consult timetables, or check for changes. The decision to travel can be immediately followed by hitting the road, exemplified by the seamless stretch of asphalt that connects destinations worldwide.

- **Versatility**
  While each transportation mode has technical constraints limiting optimal use to certain contexts, cars stand out for their versatility. They are highly adaptable to various travel needs: useful for short or long trips, commuting to work, or tourism, and capable of carrying people, luggage, or bulky items.

Mobility as a shared service Shared use of a mobility service characterizes all forms of transportation that do not involve using a personally owned vehicle. This includes traditional transportation services such as trains, subways, streetcars, buses, and cabs, as well as newer shared mobility services like bikesharing, carsharing, carpooling, and other innovative services enabled by digital platforms. These are collectively referred to as ”shared mobility services.” All shared mobility services feature an organization (ranging from simple to complex) providing a mobility service and multiple users sharing vehicles and routes. Sharing can occur in two ways: sequentially, as in carsharing or cab rides, or simultaneously, as in subway rides or carpooling.

From both a production and consumption perspective, the ”species” of shared mobility services can be divided into two main ”genres” based on service accessibility and availability:

- services offered along a predetermined route and available according to a schedule (fixed-route/scheduled);
- services not subject to these conditions, thus offered point-to-point, on demand, with routes determined as needed (on-demand).

The first category includes all guided transportation services such as railways, subways, streetcars, and fixed-route road services like urban and interurban buses. The second category encompasses taxi services, car rentals with and without drivers, and all sharing mobility services.

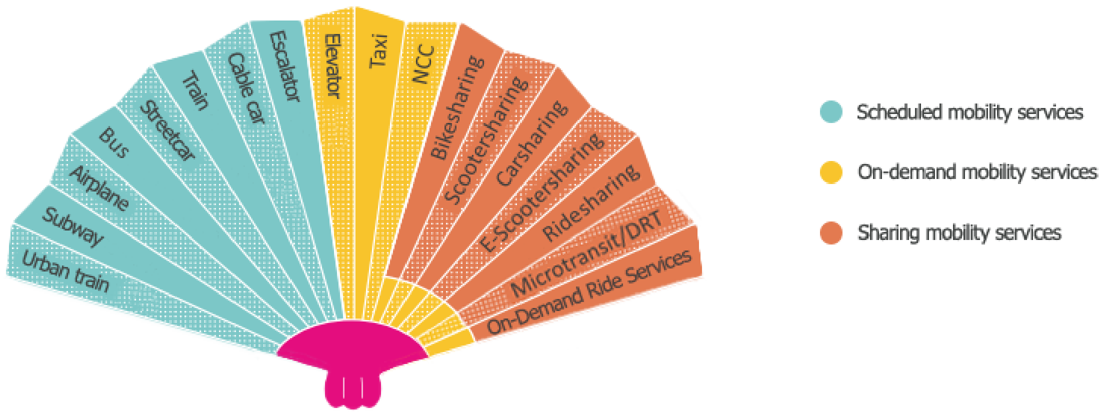


Figure 1: Visualization of shared mobility services. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

2.2.2 Characteristics of Different Scheduled Shared Mobility Services

Scheduled services are the most efficient option for quickly transporting a large number of passengers along major traffic routes, especially during peak hours. However, these services offer limited accessibility in terms of both space and time, and are characterized by discontinuity throughout the overall journey.

Figure 2: Visualization of scheduled mobility services. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

Even if not necessarily confined to tracks, separate lanes, or specific station stops, all scheduled services, whether on road or rail, must limit their availability in space and time for efficiency reasons. While more flexible than rail transport, shared road transport services still cannot match the accessibility, availability, continuity, and versatility of personal vehicles.

2.2.3 Characteristics of Different On-demand Shared Mobility Services

On-demand services, on the other hand, are capable of offering levels of accessibility, availability, versatility, and continuity comparable to using a privately owned vehicle. They can meet a demand that occurs episodically, discontinuously, and is difficult to predict.

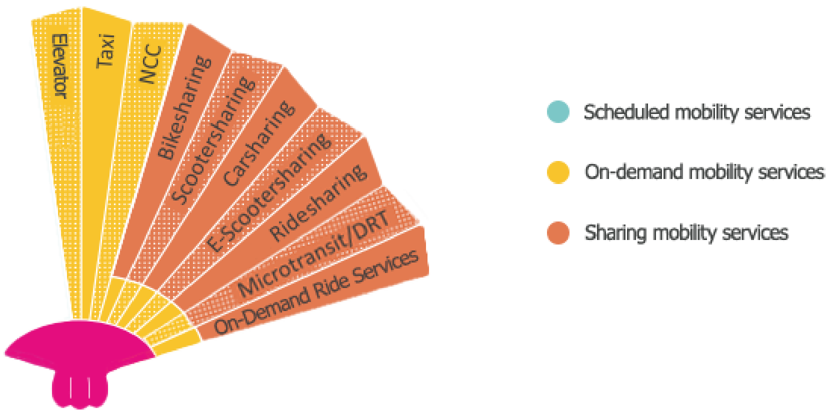


Figure 3: Visualization of On-demand mobility services. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

However, the sharing of vehicles originally designed for personal use means that on-demand mobility services cater to much lower demand volumes within the same time unit compared to scheduled transport services. Additionally, on-demand services are generally offered at higher unit prices than scheduled services operating along the same routes. The higher price, reflecting a different cost structure and the provision of a "customized" service, is advantageous for occasional use.

2.2.4 Shared Mobility Services and Their Distinctive Characteristics

According to Shaheen and Chan (2016), it is "Shared mobility is the shared use of a vehicle, bicycle, or other low-speed mode that enables users to have short-term access to transportation modes on an "as-needed" basis, often serving as a first- or last-mile connection to other modes, such as public transit."[24]. This innovative transportation method, which users can access temporarily, is changing the way people travel. What characterizes this form of mobility is the sharing of the vehicle rather than ownership, and the use of technology allows users and providers to connect.

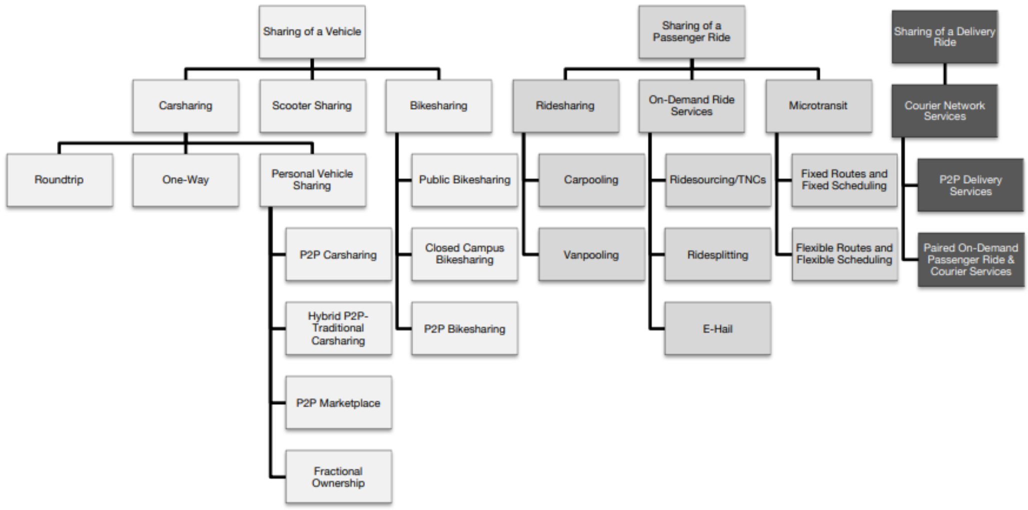


Figure 4: Map of shared mobility services. Source: Mobility and the Sharing Economy: Potential to Overcome First-and Last-Mile Public Transit Connections 2016 Shaheen Susan, PhD;Chan Nelson[24]

Like other traditional on-demand services such as taxis and rentals with or without drivers, all sharing mobility services are characterized by being available at the request of passengers, with routes and schedules determined each time. However, sharing mobility services differ from these traditional on-demand services due to the enabling power of new digital technologies. It is thanks to this fundamental technological revolution that some niche services have started to emerge as forms of mass production/consumption, and that pre-existing mobility practices or services, such as hitchhiking, car rental, and even taxi or chauffeur services, have undergone a radical transformation, evolving into services with unique characteristics. The features that distinguish sharing mobility services from both scheduled services and traditional on-demand services are as follows.

- **Networked**
  Digital platforms enable the creation of relationships and exchanges beyond physical boundaries more quickly and effectively.

- **Interactive**
  Through digital platforms, users of sharing mobility services not only have the opportunity to use but also to create/modify the service offered. The real-time interaction enabled by the platform allows providers to continuously adapt their services to meet user needs.

- **Collaborative**
  The formation of a network activates multiple forms of collaboration and coordination practices among individuals that were previously unheard of. The development of a community not only enhances the recognition and reputation of the platforms but also

provides opportunities to enable various types of transactions, including non-commercial ones based on exchange and gifting.

- **Utilization of Residual Capacity**
  Sharing mobility services are characterized by their ability to utilize the residual capacity compared to the personal and exclusive use of an owned vehicle. This increased productivity can occur during a trip—when the occupancy rate of a vehicle is increased, for example, through carpooling platforms—or over a period of time—when a vehicle reduces its idle time, especially when parked and not transporting anyone, for example, through carsharing.

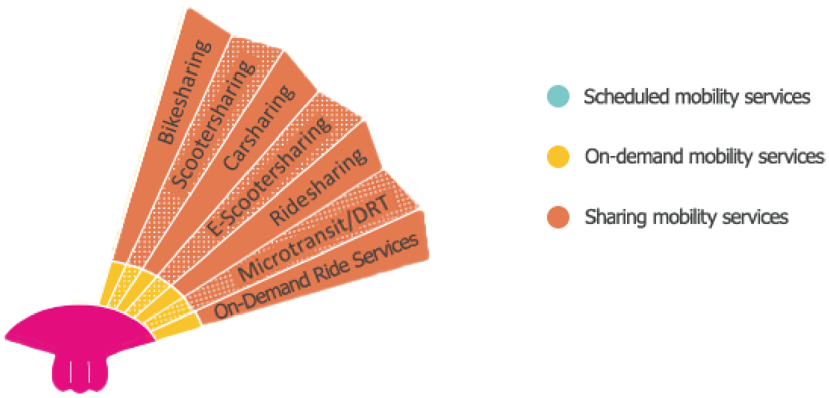


Figure 5: Visualization of sharing mobility services. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

2.2.5 Advantages of Technological Progress in Shared Mobility

Technological innovation enables sharing mobility services to offer performance comparable to traditional on-demand services at lower costs or with better performance. For vehicle-sharing services, innovations allow users to drive vehicles and make very short-term rentals automatically, without staff interaction. Consequently, vehicle-sharing services are competitively priced compared to transport services needing drivers or staff for vehicle management. In ridesharing, innovation increases the matching of supply and demand and reduces travel costs, such as carpooling trips being offered at lower prices than transport companies. Despite occasional use, sharing mobility services are becoming more frequent and widespread due to cost reductions and their ability to meet diverse, unpredictable mobility needs.

The growing number and improved performance of sharing mobility services create new opportunities for integrating shared mobility. This evolution is driven by new digital technologies and varied combinations available for users who prefer mobility services over personal transport. Integration can occur:

- Along the route (intermodality): between the origin and final destination of a trip.
- Over time (multimodality): in the sequence of repeated trips within a day, week, etc.

Sharing mobility services enhance scheduled transport services by covering the first and last mile, offering new and better travel options that compete with private vehicle trips. Full commercial integration of mobility services through MaaS platforms allows consumers to purchase multiple mobility services via a single platform and payment method. These platforms provide an intermodal journey planner, booking system, unified payment, and real-time user information, exemplified by integrated services like trains, subways, buses, taxis, carsharing, and bikesharing.

The expanded range of shared mobility services allows individuals to choose the most convenient travel solution each time, instead of relying on their own vehicle. With a wider variety of mobility options, people can select the best mode of transport for different trips, such as taking the train instead of driving to the city center or using carsharing instead of the bus at night. This integration is further supported by ”bundles” or packages of integrated mobility services offered through MaaS platforms, providing prepaid travel minutes with various services (taxi, bus, metro, carsharing), similar to a phone plan with included data, SMS, and voice minutes.

2.2.6 Environmental, Social and Economic Advantages of the Efficient Use of Intertwined Shared Mobility Services

The spatial and temporal integration of all types of shared services is a key aspect for providing an efficient service and enabling users to reduce or even forego the use of their own transportation. Expanding the overall range of shared mobility solutions and offering integrated mobility services as a substitute for private vehicle use is essential for achieving efficient, low-emission, and socially inclusive mobility. According to the OECD, if all private road traffic in a city were replaced with various integrated shared mobility services, vehicle mileage would significantly decrease, along with associated impacts such as energy consumption, pollutant emissions, congestion, and accidents.

Additionally, the much more intensive use of shared vehicles compared to private vehicles would lead to a drastic reduction in the total vehicle fleet and a different use of street space, typically reserved for parking. The OECD/ITF model[14], applied to the city of Lisbon in a simulation where motorized transport is replaced by three shared mobility services (ridesplitting, microtransit, and mass rapid transit), shows the elimination of congestion, a one-third reduction in CO_2 emissions, and a 95% reduction in public parking needs. The required transport fleet to achieve these results is only 3% of the current fleet in the Portuguese city.

Although each shared vehicle would travel about ten times more kilometers than a private vehicle, the total mileage during peak hours would decrease by 37%. Due to the much longer distances traveled per vehicle, the lifecycle of shared vehicles would be much shorter, enabling faster adoption of electrification and accelerating the reduction of CO_2 emissions from urban mobility.

The benefits for citizens are not only environmental but also social and economic. Congestion would be significantly reduced, and the provided trips would be door-to-door without transfers, drastically increasing overall accessibility to city services and ensuring greater equity of access. The simulation shows that disparities in accessibility to workplaces, schools, or healthcare services in urban areas would be eliminated. Travel costs would decrease due to the high occupancy rate of vehicles: even without public subsidies, the cost of a city trip could be reduced by up to 50% compared to current conditions. Large spaces previously dedicated to parking could be repurposed to enhance livability, such as parks, plazas, wider sidewalks, or higher-quality bike paths.

2.3 Sharing services

Shaheen and Chan describe various sharing services by distinguishing between ”vehicle sharing,” which includes carsharing, E-Scootersharing, and bikesharing, and ”passenger ride sharing,” which includes ridesharing, on-demand ride services, and microtransit (Mobility and the Sharing Economy: Potential to Overcome First- and Last-Mile Public Transit Connections (Susan Shaheen, Nelson Chan 2016)[24].

2.3.1 Sharing of a Vehicle

Carsharing Car sharing is an innovative transportation model that offers the convenience of private car use without the costs and responsibilities of ownership, providing a sustainable alternative to traditional car ownership and public transportation. Initially emerging in Europe in the 1940s, car sharing gained significant traction in the 1980s with the establishment of the first car-sharing organizations (CSOs) in Switzerland and Germany. The introduction of digital technology and smartphone apps in the 2000s made car sharing more accessible and user-friendly. There are three main types of car sharing: Round-Trip Car Sharing, where users return the vehicle to the same location, ideal for planned trips; One-Way Car Sharing, which offers flexibility for spontaneous trips by allowing users to drop off the vehicle at a different location; and Peer-to-Peer Car Sharing, where private car owners rent out their vehicles via platforms like Turo and Getaround.

The benefits of car sharing include cost savings on maintenance, insurance, and parking, reduced greenhouse gas emissions and urban congestion, less demand for parking spaces allowing cities to repurpose land, and the convenience for those who occasionally need a vehicle. However, car sharing faces challenges such as limited market penetration and awareness, varying regulatory frameworks, competition from ride-hailing services, and operational issues like fleet maintenance and vehicle availability.

The future of car sharing looks promising with the potential integration with public transit systems to enhance urban mobility, the adoption of electric and autonomous vehicles to reduce environmental impact and operational costs, and the role of car sharing in smart city initiatives. With increasing environmental awareness and supportive policies, car sharing is poised to play a significant role in achieving sustainability goals and transforming urban transportation.

Scootersharing Scooter sharing is quickly becoming a key component of the shared mobility ecosystem, offering an efficient solution for urban transportation that began to rise in prominence in the mid-2010s. Initiated by companies like Scoot Networks in San Francisco and Cityscoot in Paris, this mode of transportation leverages advancements in smartphone technology, battery efficiency, and GPS tracking to allow users to rent scooters through app-based platforms, significantly enhancing urban mobility. The system is categorized into two primary types: Station-Based, where users must pick up and return scooters to designated docking stations, and Dockless, which provides greater flexibility by allowing users to pick up and drop off scooters anywhere within a specified service area, though this can sometimes result in issues like scooter clutter and improper parking.

The advantages of scooter sharing are manifold. It provides enhanced accessibility, particularly useful for bridging the first and last mile to public transit. It reduces dependence on fossil fuels, leading to lower greenhouse gas emissions and diminished urban air pollution. It also offers an economical alternative to car ownership and ride-hailing services for short distances, and helps alleviate traffic congestion by providing a nimble and space-efficient mode of transport. Additionally, scooters offer a safer alternative to traditional motorcycles due to their lower speeds and increased stability.

Despite these benefits, scooter sharing faces several significant challenges. Safety concerns remain prevalent due to a high incidence of accidents and injuries, often exacerbated by the lack of protective gear and suitable infrastructure. The system also contends with inconsistent regulatory frameworks and varying municipal policies that can impede growth and efficient operation. High rates of vandalism and theft increase operational costs and reduce availability, and logistical issues related to maintaining and distributing scooters effectively add to the operational complexities. Moreover, while scooters help reduce emissions, their production and disposal pose sustainability challenges due to their short lifespan and the environmental impact of their materials.

Looking forward, the future of scooter sharing is promising, bolstered by technological advancements, increasing environmental awareness, and supportive urban policies. The integration of scooter sharing with public transit systems could further enhance its convenience and appeal, promoting a more multimodal approach to transportation. Advances in battery technology, GPS, and mobile applications are likely to improve scooter performance, user experience, and operational efficiency. Furthermore, efforts to extend the lifespan of scooters, improve recycling processes, and develop more sustainable manufacturing practices are critical in mitigating the environmental concerns associated with scooter sharing[25].

With ongoing support from urban policies and the integration of scooter sharing into broader smart city initiatives, the sector is well-positioned for future growth and evolution, offering a sustainable and convenient alternative to traditional modes of transportation. As cities continue to innovate and seek solutions to transportation challenges, scooter sharing stands out as a forward-thinking and adaptable mobility option.

Bikesharing Bike sharing has emerged as a transformative mode of urban transportation, offering an efficient, healthy, and environmentally friendly alternative to traditional methods. Originating in the 1960s with Amsterdam's "White Bicycle Plan" and evolving significantly in the 1990s with Copenhagen's Bycyklen, modern bike-sharing systems have expanded rapidly, especially with the launch of Paris's Vélib' in 2007, which incorporated digital technology to enhance user experience and management.

Bike-sharing systems fall into three categories: Station-Based, which involves designated docking stations for picking up and returning bikes; Dockless, offering the flexibility to pick up and drop off bikes anywhere within a designated area but can lead to clutter; and Hybrid Systems, which blend both station-based and dockless elements to provide flexibility while maintaining some organization.

The benefits of bike sharing are extensive. It promotes physical activity, enhances public health, reduces greenhouse gas emissions and urban air pollution, alleviates traffic congestion, and supports public transit systems by improving first-mile and last-mile connectivity. It also offers an affordable transportation option that contributes to societal welfare and environmental sustainability.

However, bike sharing faces challenges such as high rates of theft and vandalism, the need for dedicated infrastructure like bike lanes and docking stations, inconsistent regulatory frameworks, and maintenance and redistribution logistics. Additionally, usage can wane during adverse weather conditions, impacting its financial sustainability.

The future of bike sharing looks promising with the potential for further integration into public transit systems and enhancements from technological innovations in GPS, IoT, and mobile applications. The introduction of electric bikes (E-Bikes) is set to attract a broader demographic by easing physical exertion and expanding possible travel distances. As cities prioritize sustainable development and green transportation, bike sharing is poised for increased adoption and expansion, leveraging data and technology to optimize operations, enhance safety, and provide real-time information to users. This makes bike sharing a practical and progressive solution to urban mobility challenges.

E-Scootersharing E-Scooter sharing has quickly become a favored urban transportation solution, offering an efficient and eco-friendly alternative to traditional transport methods. Launched initially in 2017 by companies like Bird and Lime in Santa Monica, California, the system allows individuals to rent electric E-Scooters for short-term use via app-based platforms. The convenience and affordability of E-Scooters, combined with advancements in battery technology, GPS, and mobile applications, have enabled the rapid global expansion of these services.

E-Scooter sharing systems are generally classified into two types: Dockless, which allows users to pick up and drop off E-Scooters anywhere within a designated area, providing great flexibility but sometimes resulting in clutter and parking issues; and Station-Based, which requires E-Scooters to be picked up and returned to specific docking stations, offering more organized parking at the cost of significant infrastructure investment.

The benefits of E-Scooter sharing include quick and easy transportation for short distances, which is particularly useful for first-mile and last-mile connectivity to public transit. It reduces dependence on fossil-fueled vehicles, thereby lowering greenhouse gas emissions and urban air pollution. It also provides an affordable alternative to car ownership and ride-hailing services, helps alleviate traffic congestion by offering a nimble and space-efficient transportation option, and encourages outdoor activity, contributing to a more active lifestyle.

However, E-Scooter sharing also faces challenges, including high rates of accidents and injuries, inconsistent regulatory frameworks, and issues with vandalism and theft which increase operational costs and reduce availability. Additionally, the environmental impact of E-Scooter production and disposal, along with their short lifespan, raises sustainability concerns.

Looking forward, the prospects for E-Scooter sharing are promising, supported by ongoing technological advancements, increasing environmental awareness, and supportive urban policies. Integrating E-Scooter sharing with public transit systems can enhance its appeal and convenience, promoting multimodal transportation. Advances in technology can improve E-Scooter performance, user experience, and operational efficiency. Efforts to extend the lifespan of E-Scooters, along with improvements in recycling processes and more sustainable manufacturing practices, are crucial for addressing environmental concerns.

E-Scooter sharing represents a significant transformation in urban mobility, offering a sustainable and convenient alternative to more traditional transportation modes. Despite the challenges, the sector is poised for growth and evolution, driven by supportive policies and a growing focus on environmental sustainability. As cities continue to innovate and seek solutions to transportation challenges, E-Scooter sharing stands out as a practical and progressive approach to modern urban mobility.

2.3.2 Sharing of a Passenger Ride

Ridesharing has emerged as a revolutionary mode of transportation within the shared mobility ecosystem, providing an efficient, cost-effective alternative to traditional taxi services and personal car use. This system enables individuals to share rides, often coordinated through digital platforms. As cities worldwide seek to mitigate traffic congestion, reduce emissions, and enhance transportation efficiency, ridesharing has become an integral component of urban mobility strategies. This analysis explores the history, types, benefits, challenges, and future prospects of ridesharing.

Ridesharing as a concept dates back to the early 20th century, but it gained significant traction in the digital age with the advent of smartphone applications. The modern ridesharing industry began to take shape in the late 2000s with the launch of platforms like Uber (2009) and Lyft (2012) in the United States. These companies leveraged GPS technology, mobile internet, and advanced algorithms to match riders with drivers in real-time, revolutionizing the way people use transportation .

Ridesharing can be broadly categorized into three main types.

1. **Peer-to-Peer Ridesharing:** private individuals use their own vehicles to offer rides to others, facilitated by platforms such as Uber and Lyft.

2. **Shared Rides:** multiple passengers share a single ride, often at a reduced fare, with routes optimized to accommodate pick-ups and drop-offs along the way. Services like UberPool and Lyft Shared exemplify this model.

3. **Commuter Ridesharing:** organized carpooling services that facilitate regular shared

rides for commuters traveling similar routes, often coordinated through workplace programs or dedicated apps like Waze Carpool.

Ridesharing offers numerous benefits that contribute to individual convenience, societal welfare, and environmental sustainability. It reduces transportation costs for individuals by sharing expenses such as fuel and tolls among multiple passengers, which leads to cost savings. Ridesharing also lowers greenhouse gas emissions and air pollution by reducing the number of vehicles on the road, which contributes to fewer vehicle miles traveled and less environmental impact. It alleviates traffic congestion by encouraging carpooling and reducing the number of single-occupancy vehicles. Additionally, ridesharing provides a flexible and convenient transportation option that is often quicker and more responsive than traditional taxis or public transit, enhancing convenience and flexibility. Furthermore, it creates income opportunities for drivers and supports the gig economy, fostering economic opportunities.

Despite its benefits, ridesharing faces several challenges. Ridesharing services often encounter regulatory challenges and opposition from traditional taxi services, with regulations varying widely by region, which can impact service availability. The classification of drivers as independent contractors rather than employees has sparked debates over labor rights, benefits, and working conditions, raising labor concerns. Ensuring passenger and driver safety, managing incidents, and addressing liability concerns are ongoing challenges related to safety and liability. While ridesharing reduces individual car use, studies have shown that it can also increase overall vehicle miles traveled due to deadheading (drivers traveling without passengers) and induced demand, leading to environmental concerns. Lastly, intense competition among ridesharing companies can lead to aggressive pricing strategies and market monopolies, impacting driver earnings and service quality, which poses a challenge in market competition.

The future of ridesharing is promising, driven by technological advancements, increasing environmental awareness, and supportive urban policies:

- Integration with Public Transit: seamless integration with public transit systems can enhance the convenience and appeal of ridesharing, promoting multimodal transportation.
- Technological Innovations: advances in artificial intelligence (AI), machine learning, and autonomous vehicles hold the potential to further transform the ridesharing industry, enhancing efficiency and safety.
- Sustainability Initiatives: increasing focus on sustainability may lead to the adoption of electric vehicles (EVs) within ridesharing fleets, reducing the environmental impact.
- Smart City Initiatives: as cities become smarter and more connected, ridesharing can leverage data and technology to optimize operations, enhance safety, and provide real-time information to users.
- Policy Support and Regulation: supportive policies and regulatory frameworks can help address safety concerns, ensure proper infrastructure, and promote the sustainable growth of ridesharing programs.

On-demand ride services On-demand ride services have significantly transformed urban mobility since their emergence in the late 2000s, beginning with pioneers like Uber in 2009 and Lyft in 2012. Utilizing advanced technologies such as real-time GPS tracking, mobile payments, and sophisticated algorithms, these services offer a convenient and efficient alternative to traditional taxis and personal vehicle use, addressing key urban challenges like traffic congestion, emission reductions, and mobility enhancement.

The services are primarily divided into three categories.

1. **Ride-Hailing:** this is the most common form, where platforms like Uber and Lyft connect users with nearby drivers who use their personal vehicles to offer rides, summoned through a mobile app.

2. **Ride-Pooling:** platforms such as UberPool and Lyft Shared enable users to share their rides with others heading in the same direction, reducing per-passenger costs and increasing vehicle occupancy.

3. **Microtransit:** this less traditional form involves on-demand shuttles or minibuses with flexible routing and scheduling, like Via and Bridj, which are especially useful for providing connectivity to and from major transit hubs.

The benefits of on-demand ride services are manifold. They provide unparalleled convenience and accessibility, allowing users to secure transportation quickly and efficiently from almost anywhere at any time via a smartphone. Economically, they often undercut traditional taxis and can be cheaper than owning and maintaining a personal vehicle, especially in urban areas where parking and fuel costs can be prohibitive. Environmentally, by facilitating ride-sharing and reducing the need for individual car ownership, these services can contribute to lower greenhouse gas emissions and reduced urban congestion.

However, the sector is not without its challenges. Regulatory issues are a significant hurdle, with varying local and regional laws that can complicate service delivery and expansion. Labor concerns also persist, particularly regarding the status of drivers as independent contractors, which affects their rights and benefits. Safety and liability issues continue to be a concern for both passengers and drivers, alongside the environmental impact associated with increased vehicle miles traveled by empty cars (deadheading) and the demand induced by the availability of convenient rides.

Looking to the future, the prospects for on-demand ride services are robust, driven by continued technological innovations including the integration of AI, machine learning, and the impending roll-out of autonomous vehicles, which could revolutionize the industry by enhancing efficiency and reducing costs. Increasing environmental consciousness and urban policy support are likely to spur the adoption of electric vehicles within service fleets, further reducing their carbon footprint.

Additionally, as urban areas become smarter and more integrated, these services are poised to become a key component of comprehensive public transit networks, offering last-mile solutions that seamlessly connect with traditional bus and train services. Effective regulation and supportive policy frameworks will be crucial in ensuring that on-demand ride services can meet future challenges and continue to offer safe, efficient, and sustainable transportation options.

On-demand ride services thus represent a dynamic and evolving sector of urban transportation, offering significant benefits while facing manageable challenges. With proper management, innovation, and regulatory support, they stand to play an increasingly important role in shaping the future of urban mobility.

Microtransit Microtransit is reshaping urban transportation by offering a flexible, efficient alternative to traditional public transit and private vehicle use. Utilizing smaller vehicles like vans or minibuses, microtransit leverages technology to provide on-demand, dynamically routed services. This modern approach caters to the growing demand for first-mile and last-mile connectivity, enhancing overall transit efficiency and connectivity within cities.

The evolution of microtransit is closely tied to technological advancements. Although demand-responsive transport systems have been around since the mid-20th century, the concept of microtransit gained significant traction in the 2010s with the rise of digital platforms. Companies like Via, Chariot, and Bridj were pioneers, using apps to offer flexible and responsive public transportation options that traditional fixed-route buses could not match.

Microtransit generally falls into two categories.

- **On-Demand Microtransit:** this type allows users to request rides in real-time via mobile apps, using algorithms to route vehicles based on current passenger needs, exemplified by services like Via and RideCo.
- **Flexible Route Microtransit:** combining fixed-route efficiency with on-demand flexibility, this model operates along semi-fixed routes with the ability to deviate to specific areas for pickups and drop-offs, like the Kansas City microtransit pilot.

The benefits of microtransit are extensive, offering several advantages. It enhances connectivity by bridging gaps between main transit hubs and final destinations, which reduces reliance on private cars. Microtransit adapts to real-time passenger demand, providing flexibility and convenience by minimizing wait times and streamlining routes. It is more cost-effective in low-density areas compared to traditional buses, making it an economical choice. By increasing vehicle occupancy and reducing the number of vehicles on the road, microtransit also helps in cutting down congestion and emissions. Furthermore, it improves user experience through the incorporation of technology, offering seamless features like real-time tracking and cashless payments.

However, microtransit faces several challenges. Integrating with existing transit systems and navigating complex regulatory frameworks present significant regulatory hurdles. The sustainability of microtransit can be challenging due to high operational costs related to vehicle maintenance, driver wages, and technology. Attracting sufficient ridership to sustain operations, especially in less populated areas, is often difficult, impacting ridership and utilization. A heavy reliance on modern technology could alienate less tech-savvy users or those without smartphone access, leading to issues with technology dependence. Additionally, ensuring that all socioeconomic groups have access to services, particularly outside affluent or densely populated areas, remains a challenge due to equity concerns.

Looking ahead, the prospects for microtransit are promising, driven by ongoing technological innovations, increasing environmental consciousness, and supportive urban policies. Future advancements could see microtransit seamlessly integrated with larger public transit systems, enhancing multimodal transportation solutions. Developments in AI, machine learning, and potentially autonomous vehicles could revolutionize operational efficiencies. Furthermore, an increased focus on sustainability might lead to greater adoption of electric and hybrid vehicles within microtransit fleets, reducing environmental impacts.

As cities evolve and strive for smarter, more connected transportation solutions, microtransit stands poised to play a crucial role in the future of urban mobility, combining flexibility, efficiency, and sustainability. With appropriate policy support and continued technological advancement, microtransit offers a forward-thinking approach to tackling modern transportation challenges.

<table>
<tr><th>“Original” models</th><th>First evolutions</th><th>Web 1.0</th><th>Web 2.0</th><th>Next generation</th></tr>
<tr><td>Hitch-hiking</td><td rowspan="2">Slugging</td><td>Carpooling</td><td rowspan="2">Dynamic ride sharing</td><td rowspan="6">Shared driverless car</td></tr>
<tr><td>Informal shared rides between colleagues</td><td>Vanpooling</td></tr>
<tr><td>Taxi</td><td rowspan="2">Radiotaxi with phone booking</td><td rowspan="2">On-demand services (TNC)</td><td>E-Hail</td></tr>
<tr><td>Rental with driver</td><td>Ridesourcing</td></tr>
<tr><td rowspan="2">Car rental without driver</td><td rowspan="2">One-way Car rental</td><td>Station-based carsharing</td><td>Freefloating carsharing</td></tr>
<tr><td>Niche carsharing</td><td>Peer to peer carsharing</td></tr>
<tr><td rowspan="2">Public transport services in low demand areas</td><td rowspan="2">Public transport services in low demand areas with phone booked routes</td><td rowspan="2">Public transport services in low demand areas with smart display booked routes</td><td>On-demand services with ridesplitting</td><td rowspan="2">Driverless bus or minibus</td></tr>
<tr><td>Microtransit</td></tr>
</table>

Figure 6: Evolution of On-Demand Transport Services. Adapted from [17]

2.4 Sharing mobility in Italy

The latest data from the Mobility Styles Observatory[13] reveals that Italians spend an average of six hours traveling each week. 64% of these trips are made using personal cars and motorcycles, a slight decrease from the previous year, offset by an increase in the use of public transportation and electric cars (both private and rental), which rose from 11% to 13%. Travel on foot, by bicycle, or electric scooter remains stable at 22% of travel time. Additionally, travel on holidays has decreased by about 10%, often the first to be cut by those struggling to make ends meet. In cities, sustainable mobility is most prevalent in Bologna and Milan, with 49% and 48% of trips made on foot, by bicycle, or using collective or shared transport; while 40% and 45% are made using combustion engine cars and motorcycles. Higher percentages are seen in Turin (51%), Rome (54%), and Naples (55%)[13].

Mobility Type	Year	Total Minutes of Mobility	Italy	Milan	Rome	Turin	Bologna	Naples
Light Mobility	2023	22%	26% (-1%)	19%	25% (-1%)	25%	23% (+1%)	23% (+1%)
	2022	22%	27%	19%	26%	22%	22%	22%
Medium Mobility	2023	13% (+2)	22% (-2%)	19% (+1%)	13%	24%	15% (-2%)	15% (-2%)
	2022	11%	24%	18%	13%	17%	17%	17%
Heavy Mobility	2023	64% (-2%)	45% (-4%)	54% (-8%)	51% (-9%)	40%	55% (-6%)	55% (-6%)
	2022	66%	49%	62%	60%	40%	61%	61%

Figure 7: How we move: the type of mobility and its impact. Adapted from [13].

Category	Year	Italy	Milan	Rome	Turin	Bologna	Naples
% movement by private car or motor/scooter	2023	70%	58% (+3%)	65% (-1%)	66%	57%	65% (+1%)
	2022	72%	55%	66%	66%	-	64%
% movement by public transport or sharing	2023	16% (+3%)	24% (-2%)	20% (+1%)	15% (-1%)	27%	18% (-1%)
	2022	13%	25%	19%	16%	27%	19%

Figure 8: How we move: between public transport and private vehicles. Adapted from [13].

The precarious situation highlighted by the Mobility Styles Observatory is rooted primarily in the lack of alternatives to using private cars due to the distance from essential services like schools and medical facilities. Additionally, the scarcity of public transport, including inconveniently scheduled stops and a lack of sharing services, contributes to the problem. Economic conditions also play a role, making it hard for families to afford fuel costs and cope with long distances without alternatives to cars. These mobility challenges have led Italians to forgo opportunities mainly in the following areas.

- Work: 28%
- Leisure outings: 25
- Medical visits: 19
- Education: 17

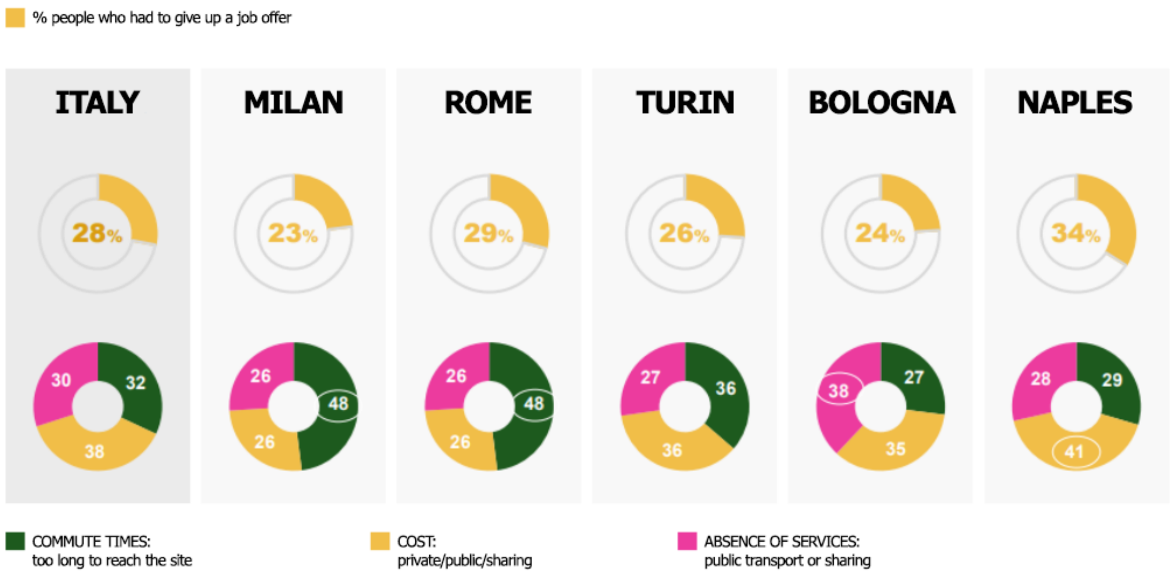


Figure 9: People who had to give up a job offer due to commuting difficulties. Adapted from ”Legambiente, Osservatorio Stili di Mobilità”[13].

Among the various types of precariousness analyzed, the most concerning statistic is the 7% of people in extreme mobility poverty, meaning they lack access to nearby public or shared transportation and cannot afford to buy a car. Other respondents report less severe but still significant issues: 9% struggle with high fuel costs relative to their income, 8% cite the absence of alternatives to private cars and/or the inability to replace outdated vehicles, and another 8% face high costs due to the necessity of long daily commutes by car.

2.4.1 Vehicle Sharing

Carsharing The 2022 data on the volume of free-floating carsharing rentals seem to confirm a new level at just over 6 million, a figure not dissimilar to that recorded at the height of the pandemic in 2020 and a long way from the 12 million in 2019. At the same time, the figure for journeys has risen again in the last year, plus 33.5% compared to 2021, almost returning to 2018 levels, confirming a radical change in the way carsharing users use carsharing mobility.

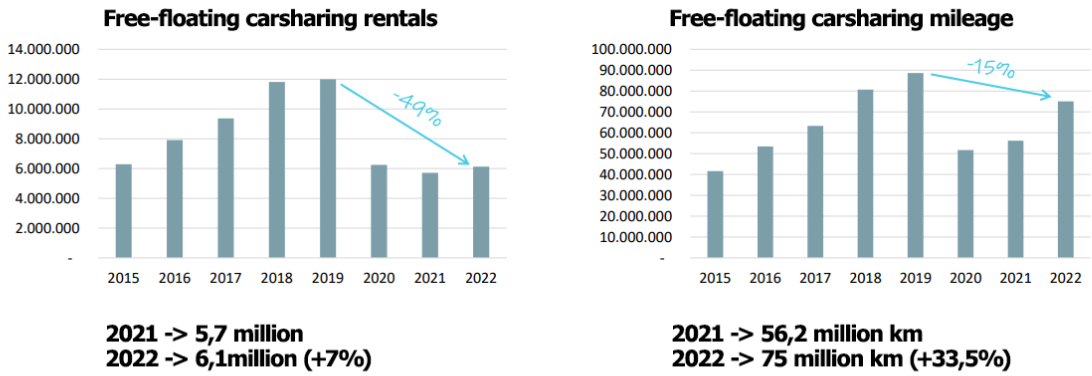


Figure 10: Free-floating carsharing demand. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

The growth trend in station-based carsharing rentals will slow down in 2022 to around 300,000 trips, a level still higher than the pre-pandemic level of 2018 and not far from the peak of 360,000 in 2019. In the case of station-based services, however, the figure for journeys in 2022 rises more sharply: 8 million km travelled, about 15% more than the previous year.

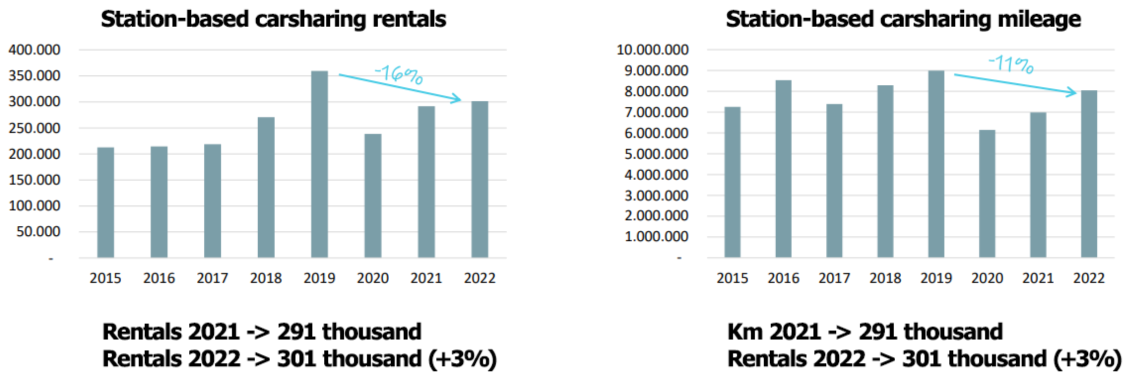


Figure 11: Station-based carsharing demand. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

The offer of free-floating carsharing in terms of vehicles available to users is still shrinking. From 5.4 thousand vehicles in 2021 to 4.7 thousand vehicles in 2022. The electrification rate improves by 15 per cent due to 520 new electric vehicles in the fleet and the simultaneous reduction of part of the internal combustion fleet. On the other hand, 2022 is the year in which station-based carsharing will see the largest number of vehicles since the beginning of the survey: 1,300 cars, 60% of which are fully electric.

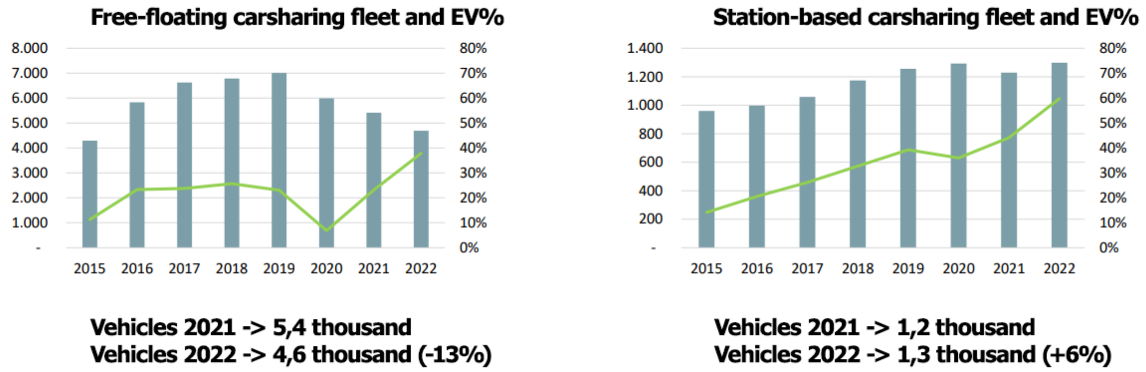


Figure 12: Free-floating carsharing fleet and EV%. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

Scootersharing Growth in demand for scootersharing is also strong for the 12 months of 2022, confirming the positive trend of recent years. The number of rentals will rise from 3 million in 2021 to almost 4.4 million in 2022, recording a growth of +42%. Equally important and positive is the number of journeys, which will reach 20 million in the last year for +39% compared to 2021.

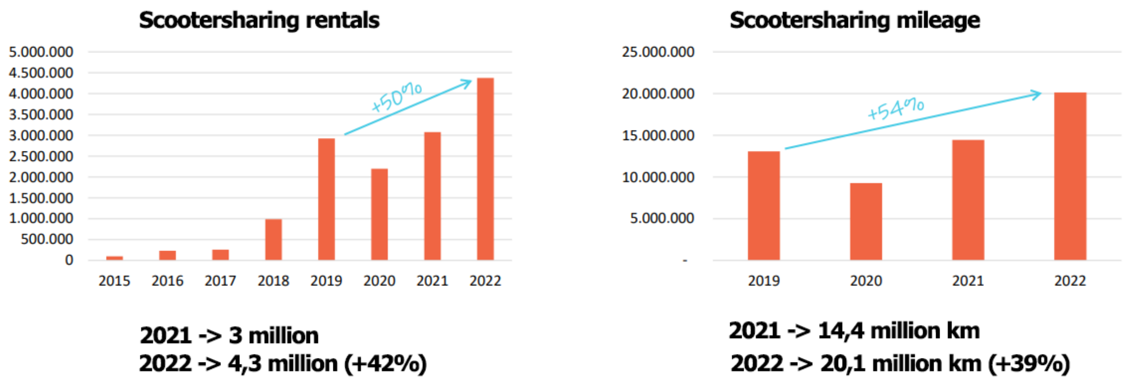


Figure 13: Scootersharing rentals. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

On the supply side, on the other hand, scootersharing services recorded their first slowdown since 2015. For the first time, the balance of active services in the last year surveyed is not higher than in the previous year (25 vs. 22). The number of shared scooters available to users also fell slightly in 2022, about 200 fewer than in the previous year.

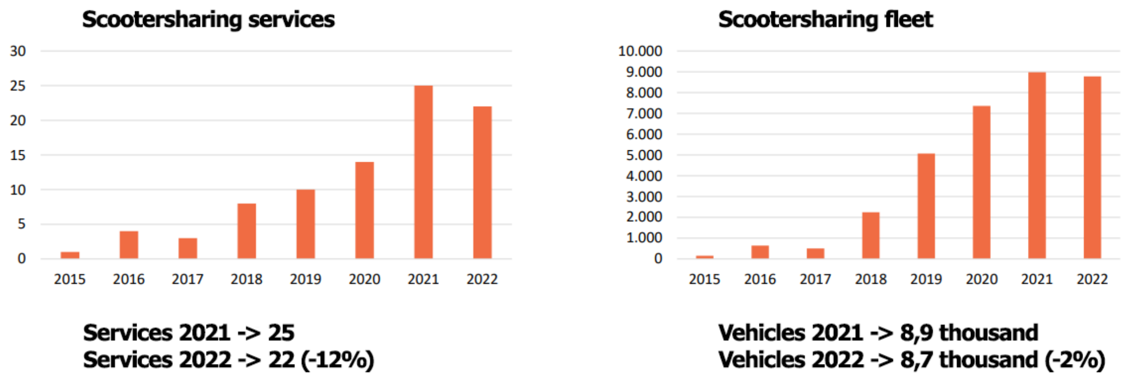


Figure 14: Scootersharing offer. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

Bikesharing 2022 proves to be an absolutely positive year for free-floating bikesharing. Nearly 9.7 million rentals, a number never recorded to date and 30% higher than the 2019 figure. Station-based bikesharing trip figures are also on the rise with a total of 4.2 million rentals, a million more than the previous year but still a million less than the pre-pandemic figure.

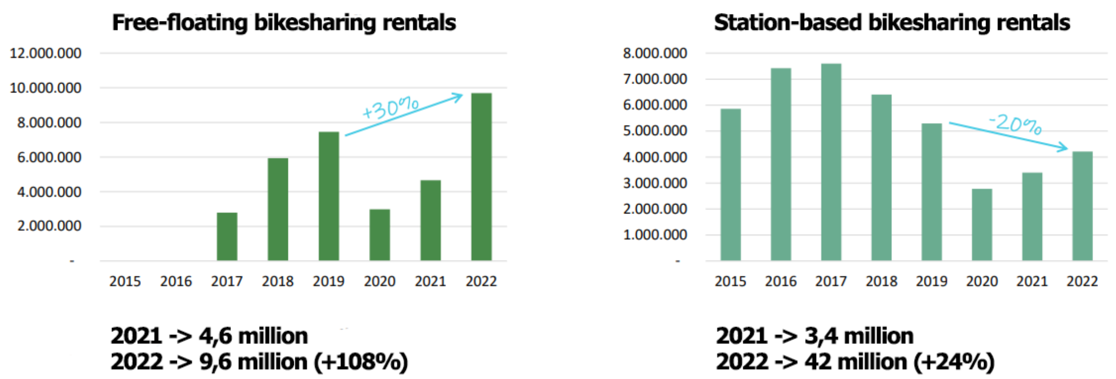


Figure 15: Bikesharing rentals. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

The total number of bikesharing services increased, albeit slightly, from 38 to 41 active services in 2022, mainly due to new openings in free-floating services (+6 services in 2022 compared to 2021), which offset a slightly negative balance for station-based services (-2 services in 2022). The number of free-floating shared bikes doubles (39,000 bikes in 2022) while the number of bikes in station-based services remains more or less stationary at 9,000.

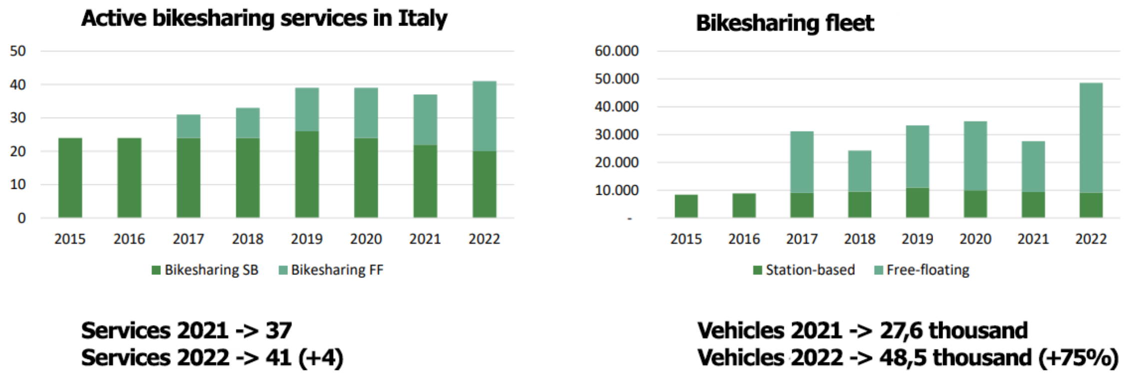


Figure 16: Bikesharing offer. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

E-Scootersharing In line with the previous year, single-vehicle sharing is the most used service in Italy when looking at the number of rentals in 2022. Twenty-five million rentals represent 50% of all rentals made by vehicle sharing services in our country, 38.8% more than in 2021. This trend also corresponds to an increase in mileage to over 60 million km in 2022.

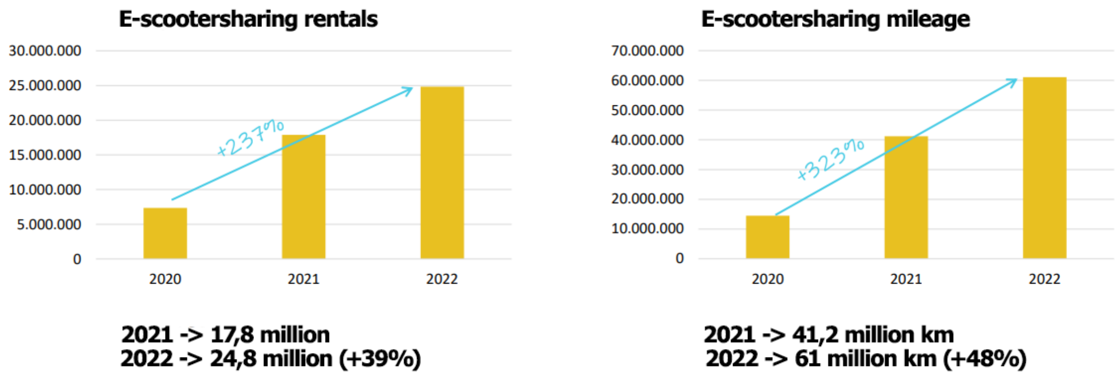


Figure 17: E-scootersharing rentals. Adapted from ”Osservatorio Nazionale Sharing Mobility”[20].

The offer of sharing scooters in Italy is growing, extending to many new Italian municipalities where sharing mobility had never yet arrived. The balance of active services in 2022 is positive by 15 units, which corresponds to a further expansion of the fleet from 46,000 to almost 50,000 vehicles in the past year, growing by 8.4 per cent year-on-year and tenfold compared to 2019.

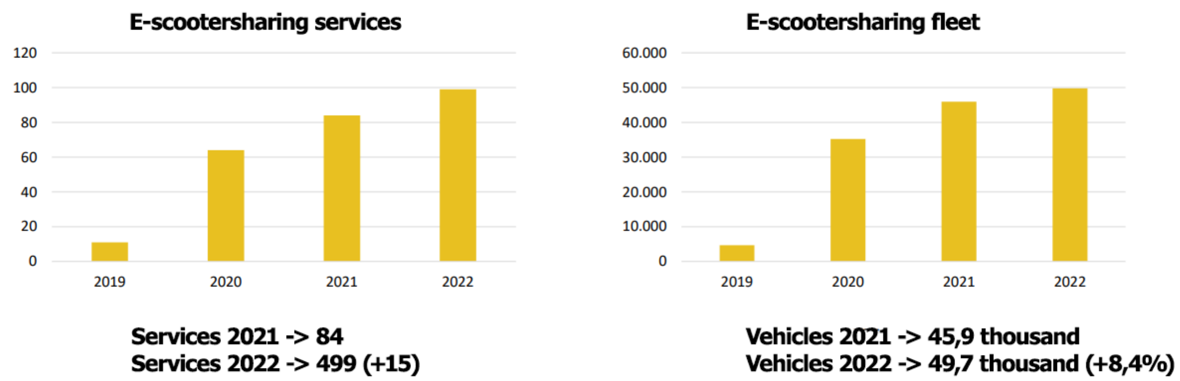


Figure 18: E-scootersharing offer. Adapted from "Osservatorio Nazionale Sharing Mobility"[20].

2.4.2 Passenger Sharing

Savings and Environmental Benefits In 2023, carpooling removed 212,410 vehicles from Italian roads, saving a total of 4,931,175 km traveled and preventing the emission of 641,135 kg of CO2. This resulted in significant savings for commuters, who avoided costs related to fuel, tolls, and parking, amounting to a total savings of 986,263 euros. Notably, Millennials are the most inclined to use carpooling, representing 62% of shared trips.[4]

Geographic Distribution and Habits of Carpoolers Regionally, Jojob's corporate carpooling is widely used across Italy, with a higher concentration in the North (63.9% of trips)[15]. The most active regions are Piedmont, Emilia Romagna, and Veneto, while the leading provinces are Turin, Alessandria, and Bologna. The provinces excelling in shared trips, economic savings, and CO2 reduction include Turin, Alessandria, Bologna, Rome, and Treviso. The average carpool trip is 26.6 km, with an average of 2.32 people per vehicle. Longer trips are noted in Liguria, averaging 47.8 km, nearly double the national average, followed by Marche (47 km) and Umbria (39.2 km). The shortest trips are in Trentino Alto Adige, averaging 19.8 km. Most trips occur on weekdays for commuting, with Tuesday, Wednesday, and Thursday being the most frequent days for carpooling.

Region	Total Trips	Km	€	Kg CO2
Piedmont	116,079	1,433,787	286,839	186,430
Emilia-Romagna	57,59	592,603	118,685	77,049
Veneto	47,321	477,632	95,505	62,106
Lombardy	46,14	618,993	123,619	80,475
Lazio	44,605	817,017	163,392	106,225
Umbria	12,86	271,071	54,174	35,245
Trentino-South Tyrol	11,458	114,959	22,994	14,942
Tuscany	9,979	146,039	29,241	18,987
Abruzzo	9,296	160,688	32,125	20,890
Campania	8,901	125,377	25,073	16,303
Friuli-Venezia Giulia	3,518	59,215	11,835	7,696
Liguria	3,21	73,351	14,709	9,538
Sicily	1,025	18,597	3,721	2,419
Apulia	481	6,204	1,241	806
Molise	434	5,814	1,163	756
Basilicata	404	3,301	660	429
Marche	339	5,372	1,074	698

Figure 19: Corporate carpooling in the Italian regions. Adapted from [15].

2.5 Carpooling

Carpooling is a form of shared mobility in which multiple passengers share a journey in a single vehicle, often a private car, to reach a similar or exactly the same destination. This practice can be informal, organized among friends or colleagues, or formal, organized through digital platforms that match passengers with drivers based on their routes and schedules. Key Aspects of Carpooling:

- **Efficiency and Cost Reduction**
  Carpooling increases the number of people traveling in a single vehicle, thereby reducing the per-person travel costs and the overall number of vehicles on the road[25].

- **Environmental Impact**
  By decreasing the number of vehicles in use, carpooling contributes to lower greenhouse gas emissions and reduced fuel consumption, aligning with broader environmental sustainability goals[13].

- **Social and Behavioral Factors**
  Carpooling also incorporates social interactions and trust among participants. It requires coordination and often a willingness to adjust schedules and routes, necessitating reliable communication channels[25].

- **Technological Platforms**
  Modern carpooling is heavily supported by digital platforms that use algorithms to match riders with drivers, manage schedules, process payments, and provide real-time updates. These platforms also enhance the safety and reliability of carpooling by allowing users to rate each other and by verifying user identities[26].

- **Regulatory and Policy Frameworks**
  Effective carpooling systems may require supportive policy environments that encourage shared rides over individual vehicle use. This can include high-occupancy vehicle (HOV) lanes, parking incentives at workplaces, and integration with other public transit systems[26].

- **Urban Planning Implications**
  Carpooling has significant implications for urban planning. Cities can plan infrastructure and transit oriented developments that support the logistics of carpooling, such as convenient pick-up and drop-off points, and integration with other modes of public transportation[13].

2.5.1 The origins of Carpooling

Carpooling, as a formal concept, can be traced back to the early 20th century but became notably popular during periods of resource scarcity, such as during World War II and the 1970s oil crisis.

The origin of modern carpooling is often linked to the economic pressures of the 1914 recession and the advent of affordable automobiles like the Ford Model T. In San Francisco around this time, car owners began offering rides in their vehicles for a small fee, equivalent to the streetcar fare, popularly referred to as ”jitney” services. This form of early carpooling spread rapidly across the United States but faced significant resistance from established streetcar operators and local governments, leading to restrictive regulations that curtailed its growth. The concept saw a resurgence during World War II, driven by government campaigns to conserve resources for the war effort. This era witnessed significant promotional efforts, including the famous ”When you ride alone, you ride with Hitler” campaign, which encouraged Americans to share rides to save resources. Carpooling received a further boost during the 1970s when the oil crisis prompted renewed governmental support through incentives for ridesharing to conserve fuel and reduce dependence on oil imports[5].

2.5.2 Types of Carpooling

Ride-sharing is usually associated with carpooling companies and is divided into two other categories: one that operates on medium- and long-distance routes, i.e., suburban carpooling, and one that operates in a peri-urban context, i.e., corporate carpooling.

Suburban Carpooling One form of car sharing with a longer history in Europe and Italy is the approach of sharing a longer (i.e., suburban) trip to increase vehicle occupancy and share costs. Several companies work to facilitate this process through websites that connect drivers with passengers. The largest of these is BlaBlaCar, a carpooling web platform operating in 22 countries with 80 million users worldwide in 2024[2]. This mobility service is based on a classic P2P marketplace: drivers can list empty seats on the platform with information about the vehicle and themselves. BlaBlaCar works as an intermediary, providing no cars or drivers. Passengers who need a ride search for suitable offers and contact the driver; in this sense, the service is supply-driven, that is, driven by the supply of rides, and contrasts with the on-demand model that governs ride hailing companies such as Uber instead. BlaBlaCar ensures that passengers pay only a fee to cover reasonable expenses, such as the car owner’s fuel, highway tolls, and wear and tear on the car. This fee is set by the driver but cannot exceed a ceiling set by the platform so as to ensure that they do not profit from the activity. The profile of out-of-town car pooling users in Italy turn out to be substantially under 40 in 70% of users, especially 50% very young under 30, and more male (57% vs. 43% female users)[15].

Corporate Carpooling Regarding corporate carpooling, this service is aimed at individual workers who need to travel affordably without their cars to get to work and at companies themselves so as to implement the practice within their own organization. In fact, companies and operators jointly implement incentive plans for employees to share home-work trips. One of the leading companies in the market for this service in Italy is Jojob launched in 2015 by the company founded two years earlier in Turin.

2.5.3 The evolution of carpooling

Carpooling is an established practice that offers significant benefits in terms of environmental sustainability, economic efficiency, and traffic reduction. With the continual evolution of technologies, the future of carpooling looks even more promising, with potential developments that could radically transform it. Below, we explore some of the possible future evolutions of carpooling, amplified by technological advancement.

Integration with Artificial Intelligence (AI) Artificial intelligence could revolutionize carpooling by significantly improving the efficiency of matching systems. More sophisticated algorithms could more accurately predict the demand for shared rides, optimizing routes in real time based on traffic conditions, passenger schedules, and travel preferences. This would not only reduce waiting and travel times but also increase the attractiveness of carpooling as a convenient and fast alternative to individual transport.

Autonomous Vehicles The evolution of carpooling could be strongly influenced by the adoption of autonomous vehicles. Driverless cars, once fully integrated into carpooling fleets, could drastically reduce operational costs and increase road safety. Furthermore, autonomous driving could facilitate the scheduling of more efficient pickups and drop-offs, improving the overall user experience and allowing vehicles to serve more passengers with less downtime.

Blockchain-Based Carpooling Platforms Blockchain technology could be used to create more secure and transparent carpooling platforms. These platforms could use smart contracts to automatically manage payments, fuel cost distribution, and other shared expenses while ensuring user data privacy and security. Additionally, a decentralized feedback system could help maintain a trustful and reciprocal environment among users.

Multimodal Integration The future of carpooling will likely see closer integration with other forms of public and private transportation. Mobility apps could evolve into comprehensive platforms offering multimodal travel solutions, combining carpooling, bike rentals, public transport, and other mobility services with a single payment and booking system. This holistic approach would facilitate the planning of more efficient and personalized journeys, promoting the widespread use of shared transportation.

Sustainability and Electric Vehicles As environmental concerns grow, it is likely that carpooling will evolve to include more electric vehicles (EVs). Adopting EVs in carpooling services would not only further reduce carbon emissions but also maintenance and operational costs, making carpooling even more affordable and accessible.

2.6 Research on carpooling in literature

2.6.1 Sample surveys

Bearing in mind that the landscape of studies on this topic is very sparse, the three studies by Ademe (French Environment and Efficient Energy Management Agency)[1] cited in the Report of the Osservatorio Nazionale Sharing Mobility (2016)[17] represent, in terms of depth and sample size, a point of reference. They are the following surveys:

- Survey of long-distance carpool users, the results of which were published during 2015;
- National study on short-distance carpooling, also published in 2015 and which refers to a series of surveys conducted during the previous year;
- National study on short-distance carpooling, published in 2015 and where there is a methodological approach on the assessment of carpooling impacts on air pollutants and CO2 emissions.

The first study examines the use of long-distance carpooling through a survey conducted among users of platforms like BlaBlaCar, LaRoueVerte, Covoiturage Grand Lyon, and IDV-ROOM. It identifies user profiles and assesses the impact of carpooling on other transportation modes and energy consumption. The longitudinal survey focuses on drivers and passengers. Before using carpooling, 67% of passengers used their vehicles, 24% used trains, 1% used buses or planes, and 8% wouldn't have traveled. Among drivers, 16% previously used their vehicles, 69% used trains, and 12% wouldn't have traveled. The study reveals that long-distance carpooling optimizes car use by increasing the average number of passengers to 3.5 per vehicle and competes with high-speed trains.

The Ademe survey estimates reductions in private car, train, and air travel distances, correlating with a 4% decrease in vehicle mileage. Every kilometer shared in a carpool equates to a reduction of 2 km of train travel and 0.07 km of air travel. This translates to a 12% reduction in CO2 emissions per carpooling crew, compared to the emissions generated by individuals before carpooling.

Ademe's second survey is conducted on a sample of about 500 short-distance carpooling users dedicated to a segment of users who use this service primarily to make home-work-home trips. Again, the survey is longitudinal in nature and requires respondents to describe their behaviors prior to using carpooling. In this case, 90 percent of respondents said that they previously used their own vehicle, 3 percent used public transportation, and the remaining share did not make the commute at all. These values reveal how short-distance carpooling, dedicated to systematic home-to-work travel, has a larger impact in terms of reducing vehicular travel than 53 medium- and long-distance carpooling. However, this is a percentage reduction on trips that are shorter on average anyway.

Ademe's third study, on the other hand, is based on a series of both longitudinal and cross-sectional surveys of multiple samples of users of a short-distance carpooling service. In a nutshell, the reduction in vehicular trips is smaller than in previous studies. What is new compared to previous studies is the estimated CO2 reductions for home-work trips, which are about 30 percent.

2.6.2 Traffic Simulation Models

Among the methods of assessing the impacts related to the use of Sharing mobility services, in addition to sample surveys, some studies using traffic simulation models have also been considered. This second group of studies, which is examined in this section, focuses on the different variants that on-demand transportation or on-demand ride service can take. These are generally transportation-based investigations to assess the impacts on a city's transportation network associated with the use of a transportation system that progressively evolves from its current technical and organizational potential, thus with driver-driven cars, vans and minibuses, toward the full use of driveless technology. Indeed, the use of traffic models instead of surveys is motivated by the fact that this type of service is not yet widely deployed and that self-driving vehicles are still at the prototype stage. These are therefore studies that foreshadow a technical scenario of the near future, which nevertheless has an interest in this chapter because it allows us to capture the impact of a massive diffusion of Sharing mobility systems. Indeed, the future prospects are that innovative shared mobility services will move from playing a complementary role to other more traditional forms, such as current public transportation services, to becoming the main form of travel in cities in the near future. The studies reviewed include:

1. Three regional cases: a medium city (Ann Arbor, Michigan), a low-density suburban area (Babcock Ranch, Florida), and a high-density urban area (Manhattan, New York). These simulate a shared autonomous vehicle fleet with a centralized routing system (Burns, 2012, Columbia University)[3].

2. Taxi-pooling in New York City explores ridesplitting using existing taxis (Santi, 2014)[21].

3. Singapore's removal of all private cars replaced by a fleet of driverless shared cars, called Automated Mobility on Demand (Spieser, 2014)[33].

4. A theoretical context similar to Austin, Texas, using Shared Autonomous Vehicles (Fagnant, 2015)[9].

5. Lisbon models two services: TaxiBot (ridesplitting minibus) and AutoVot (carsharing), simulating both current technology and autonomous driving (OECD/ITF, 2015)[14].

These studies highlight the potential for shared autonomous vehicle systems to improve urban transportation efficiency and reduce private car usage. In the five studies just mentioned, the impact indicators that are considered are:

- the total volume of mileage traveled

- the size of the simulated car fleet and consequently the potential reduction of the current car fleet
- the extent of parking spaces freed up by flows of cars that are almost always on the move
- the modal split between innovative vehicles and rapid mass transit systems
- the type of vehicles used distinguished by maximum capacity; the occupancy rate of each vehicle
- the comparative travel costs between conventional car and innovative vehicles

Among the various studies analyzed, the Lisbon one is the most useful with respect to the type of evaluation that is done within this thesis. The services that are simulated in the Lisbon case are of two types:

Displacement sharing system where travelers share time, space and resources, traveling in the same car simultaneously up to the maximum capacity of the vehicle41 which the study calls by the name of Taxi Robot or TaxiBot.

Carsharing system where travelers sequentially share a vehicle that is called the Automated Vehicle Robot or AutoVot system and is owned by an operator.

In both cases the vehicles are called with an App-based system, controlled and directed by a centralized entity that, in the case of Taxibots precisely provides for regulating the access of additional travelers besides the first one, according to a set of rules that assesses the time and maximum distance of deviation. The model also identifies situations where the vehicle is not engaged due to lack of demand and, in the case of electric drive, employs this dead time for charging. The simulation model used assigns to the two types of service the set of all origin-destination trips that are made in Lisbon today, including those made in public transport services (except metro trains and subways), and calculates the flows of shared vehicles on the road network, the location and, in the case, of Taxibots, the number of occupants of individual vehicles.

The analysis of the simulation results for the city of Lisbon shows that:

- the complete replacement of the traditional fleet with demand-driven shared vehicles (with or without autonomous driving) would result in the elimination of up to 90 percent of the current fleet with the same transport demand, quality and travel time. The reduction is much greater in the case of using ridesharing vehicles than in the case of using a carsharing service
- the reduction in vehicles would result in a reduction of parking spaces by up to 80 percent of the current area

- traffic flows along the road network may vary significantly but depending on the systems used and the combination of modes. The combination of ridesharing vehicles with a mass rapid transit system would reduce peak hour vehicles by up to 65 percent. Conversely, the use of carsharing alone would increase the number of vehicles on the road during peak hours by up to 103%

- the attractiveness of the system, the lowering of the cost per kilometer, the quality of the service offered in addition to repositioning routes and detours to pick up other passengers would result in an increase in the number of total kilometers traveled: +6% in the case of Taxibots and +89% in that of Autovots

- the introduction of electric drive is an integral and indispensable part of these transportation services

All the studies highlight an increase in vehicle mileage due largely to rebound effects. Greater efficiency and effectiveness of a transportation system based on sharing and autonomous driving, coupled with a reduction in mobility costs, tends to induce an increase in transportation demand and a consequent increase in vehicular mileage. Conversely, a shared mass transportation system based on a combination of demand-driven systems (carpooling and carsharing) is extremely more efficient, spatially, allowing for a general increase in accessibility in urban areas but always if complementary to a rapid mass transit system capable of absorbing the large traffic flows concentrated in certain hours of the day and on certain arcs of the road network.

2.7 Mobility in Genoa

The preliminary strategic framework for developing the Sustainable Urban Mobility Plan (PUMS) of the Metropolitan City of Genoa, prepared by CIELI (Italian Centre of Excellence in Logistics, Transport, and Infrastructure)[23], examines Genoa's mobility landscape. This analysis considers both challenges and positive aspects, as well as major trends that will transform mobility in the coming decades. The analysis is summarized in a SWOT framework (strengths, weaknesses, opportunities, and threats) and aligns with advanced mobility policies outlined by national and European guidelines.

2.7.1 Strengths

Genoa's mobility shows a high "self-containment" of traffic flows, with 70% of trips occurring within the city. The city boasts one of the lowest motorization rates among metropolitan cities. Public transport plays a significant role, accounting for 32% of internal city trips, and the metro line is widely used. Non-motorized transport, including bicycles and pedestrian mobility, represents a notable 23.8% of trips[23]. Increasing tourism is driving demand for varied and non-systematic mobility options, mirrored by the growth in passenger traffic at ports and the airport. Genoa and its initiatives enjoy relatively high visibility in national and sometimes international media.

2.7.2 Weaknesses

The modernization and development of railway and metro networks have been slow and uncertain. Public bus transport is perceived as slow and uncomfortable, leading to a decline in passenger numbers and financial challenges. Only 1% of commuters from outside Genoa use the bus, and there is a lack of sufficient parking for private cars, particularly interchange parking[23]. Bike sharing and car sharing have been ineffective, and taxis are underutilized. The infrastructure for non-polluting energy sources, such as electric and methane, is absent or insufficient. The San Fruttuoso area, lacking rail connections, is the primary origin of internal city trips. Critical road access points and peripheral, hilly, and valley areas, as well as some coastal towns within the metropolitan area, suffer from inadequate rail service and no viable alternatives to private cars. Pollution levels regularly exceed limits, and the increasing registration and use of freight vehicles contribute to congestion, particularly in the Val Polcevera area and at the Genoa Ovest and Bolzaneto toll booths. The mix of urban and port traffic can lead to peaks and emergencies that are difficult to manage.

2.7.3 Opportunities

The most evident traffic congestion occurs where there are no valid public transport solutions, presenting opportunities for future interchange parking. There is significant potential for growth in public transport to Genoa. The recent merger of two transport operators will optimize service across a larger area. The strong propensity for developing sharing mobility offers substantial room for improvement, and there is a good tendency towards spontaneous carpooling. Innovative collaborations between different actors in the mobility interconnection process can enhance flow integration and reduce private traffic. The polarization of O/D flows in freight traffic allows for precise, targeted policies. European experimental projects in electric mobility, such as Elviten (H2020), offer additional potential. Growing tourism and Genoa's media visibility enable the development of "social" mobility, benefiting residents and tourists alike.

2.7.4 Threats

Uncertain timelines and development processes for crucial infrastructure projects, particularly the restructuring of the railway hub, pose significant threats. The explosive growth of e-commerce could lead to uncontrollable increases in freight traffic. Urban transformations and new settlements may generate unmanageable demand for mobility. Urban sprawl in newly expanding areas often occurs in zones difficult for public transport to reach. The ongoing and anticipated growth in port traffic, especially with larger ships, can strain city mobility. The necessary revolution in the mobility system faces several challenges, including a lack of comprehensive vision, financial burdens, outdated public mindset on new mobility possibilities, corporate resistance to innovations (such as construction and competition), and bureaucratic/administrative complexities in decision-making processes. Technological improvements in vehicles, such as automation, energy, and connectivity, could widen the quality gap in favor of private transport if not effectively integrated into public transport.

3 Discrete Event Simulation of Carpooling Systems

3.1 Basics on Discrete Event Systems

3.1.1 Understanding Discrete Event Systems

Discrete event systems (DES) are a class of dynamic systems characterized by the occurrence of discrete events at specific points in time that abruptly change the state of the system. Unlike continuous systems where changes occur over uninterrupted spans of time, discrete event systems are driven by instantaneous events that trigger state transitions. Each event in a DES is a discrete interaction that happens independently, affecting the overall system based on its timing and sequence. This form of simulation is advantageous for analyzing systems where the state changes are event-driven and can be distinctly identified and recorded, making it easier to isolate impacts and investigate causal relationships between events. In DES:

- **Event Occurrence**
  Each event occurs at a specific moment, causing a change in the system state. This could include the start or end of a process, arrival or departure of entities, or changes in system resources.

- **State Variables**
  These are variables that capture the current status of the system, updating only in response to events. For example, in a traffic system, this could be the number of cars on a road segment or the status of a traffic light.

- **Event List**
  DES maintains an active list of future events, which dictates the simulation flow. The system progresses by jumping from one event to the next, which efficiently simulates systems where changes are sporadic and non-continuous.

- **Randomness and Stochastic Behavior**
  Many DES models incorporate randomness in the timing and occurrence of events, reflecting the uncertainty and variability of real-world systems. This is particularly relevant in traffic simulations where factors like vehicle arrivals and delays are not deterministic.

3.1.2 Applicability to Carpooling Simulations

Carpooling within an urban traffic network is particularly well-suited to DES because it involves clear, discrete interactions that occur at specific times and locations, such as the arrival and departure of vehicles, and the picking up and dropping off of passengers. Modeling carpooling as a discrete event system allows for detailed observation and analysis of how specific interactions influence broader system metrics such as route efficiency, travel time, and system throughput. It provides a powerful framework to explore how adjustments in carpooling operations (like changes in pickup locations or schedules) can lead to improvements in overall system performance. This event-centric approach of DES, facilitated by ExtendSim, provides the precise tools needed to dissect complex interactions within the carpooling network, enabling a deeper understanding of operational dynamics and offering strategic insights for enhancing transportation efficiency.

3.1.3 Introduction to Simulation Software

For the simulation of complex transportation networks, such as those involved in urban carpooling systems, this research utilizes ExtendSim, a leading software renowned for its robust capabilities in discrete event simulation. ExtendSim is particularly favored for its versatility and precision in modeling a wide range of discrete event systems, making it an exemplary tool for this study.

3.2 Carpooling Model

3.2.1 Main Carpooling Dynamics

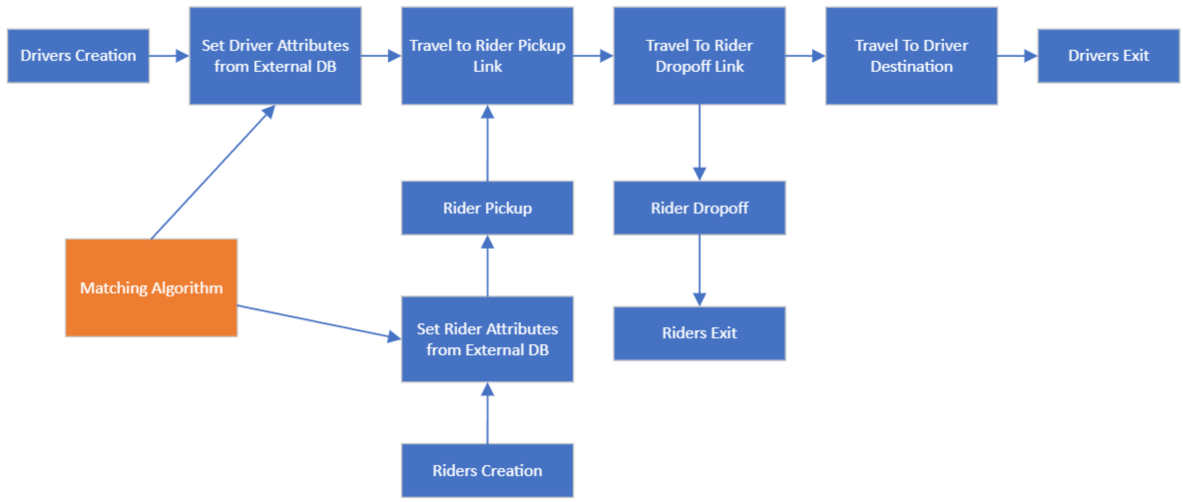


Figure 20: Flowchart of the entire model

The flowchart above presents a generalized model of a carpooling system, describing the sequential operations for both drivers and riders within the framework. It begins with the creation of driver profiles. Each driver's attributes are initialized based on information retrieved from an external database, ensuring that the data aligns with real-world characteristics and constraints.

Simultaneously, rider profiles are created following a similar procedure. Attributes for each rider are set by pulling data from the same external database.

Following the initialization phase, the flowchart depicts the travel process starting with the driver departing from an origin point. The driver proceeds to a designated pickup link, a specific location where the rider is waiting. Upon arrival at the pickup link, a pickup activity is executed, where the rider boards the vehicle.

After the pickup, the driver and the rider travel together towards a dropoff link. Once they arrive at the dropoff link, a dropoff activity is performed, marking the completion of the rider's journey.

The final segment of the flowchart illustrates the driver's continuation to their own final destination. This represents the conclusion of the carpooling cycle for the driver and their exit from the model.

3.2.2 Detailed Simulation Model

In this section it's presented a more detailed description of the carpooling model, using flowcharts to show all the mechanisms that compose the system. In the following flowcharts there are also hierarchical blocks, that are shown in green. These blocks are components in a diagram that contain other nested blocks, simplifying complex systems into more manageable sub-processes. Each of the hierarchical blocks will be described individually.

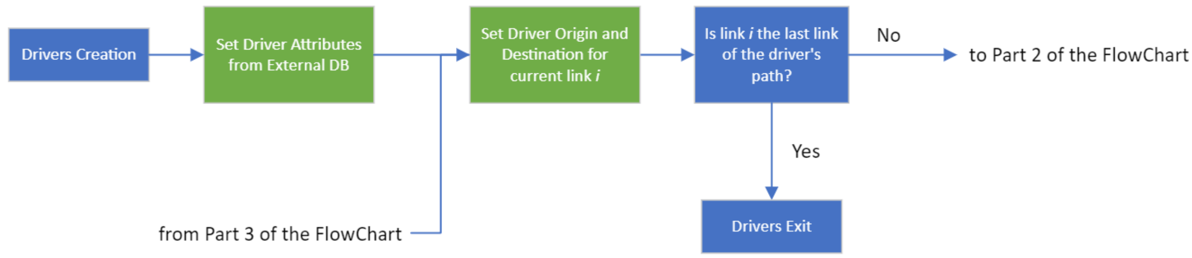


Figure 21: FlowChart Part 1

The flowchart above delineates the process of creating drivers and setting their journey parameters within the carpooling model. The process begins with the creation of drivers. The next step involves setting the driver attributes. These attributes include crucial information such as the start time, the origin and destination of the driver's path, the pickup link (where the matched rider needs to be picked up) and the dropoff link (where the matched rider needs to be dropped off), which are sourced from an external database. This external database ensures that the data reflective of real-world conditions.

Following the attribution setup, the flowchart depicts the process of assigning the origin and destination for the current link in the driver's path, also retrieved from the external database. This step is crucial as it defines the immediate route the driver will undertake.

A decision block then evaluates whether the last link traveled by the driver was the final segment of their intended route. If so, the driver is directed towards the Drivers Exit, signaling the completion of their routes. However, if there are more links to be traveled, the driver needs to perform another cycle of the system. This looping mechanism is depicted by an input arrow coming from Part 3 of the flowchart, illustrating the cyclical nature of the driver's journey within the system.

At this initial point, if the driver has more links to travel, they proceed to Part 2 of the Flowchart.

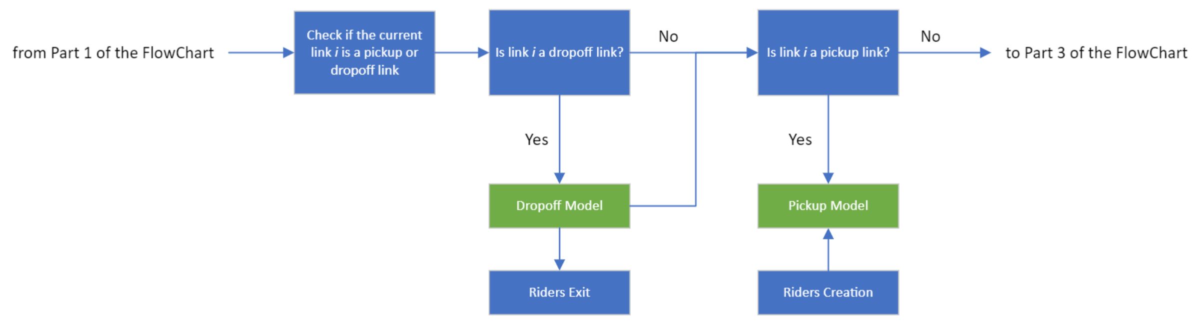


Figure 22: FlowChart Part 2

Thie flowchart above outlines the decision-making process for drivers regarding rider pickups and dropoffs. It begins by checking two main attributes of the driver: 'Pickup' and 'Dropoff'.

If the 'Dropoff' attribute is set to 1, indicating that the driver is at a stage in their route where a rider needs to be dropped off, the driver proceeds into the Dropoff Model. This hierarchical block encompasses the detailed steps involved in dropping off the rider, who then exits the system at their desired destination.

Conversely, if the 'Pickup' attribute is set to 1, this signals that the driver is at a location where a rider is waiting to be picked up. The driver then enters the Pickup Model, another hierarchical block that handles the pairing and integration of the rider into the current journey. Once paired, the driver and the newly joined rider continue their journey together.

Both the Pickup and Dropoff Models are further described later. These models are represented as hierarchical blocks within the flowchart, indicating that they contain a series of nested blocks or steps that detail the specific processes involved in each activity.

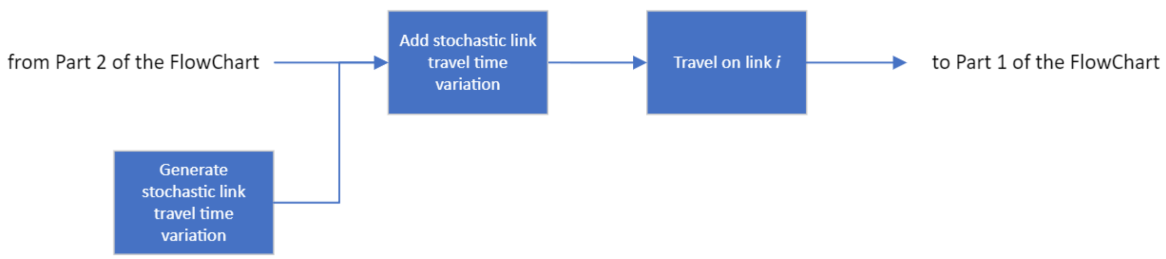


Figure 23: FlowChart Part 3

The flowchart segment above details the travel process of the driver along the current link in their route. Initially, the travel time associated with the link is retrieved from an external database. This database provides baseline travel times under typical conditions, ensuring that the model reflects realistic driving durations.

Following this, the model introduces a degree of realism by adding a random variation to the baseline travel time. This variation simulates potential delays due to traffic dynamics and congestion, factors that can unpredictably affect travel times on a day-to-day basis. By incorporating these variations, the model aims to mimic real-world driving conditions more accurately, providing a more robust simulation of driver experiences within the carpooling system.

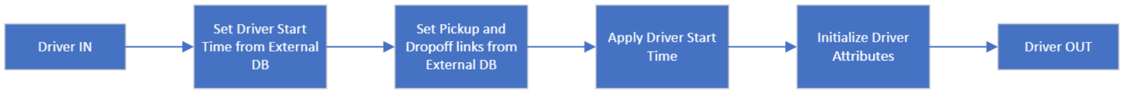


Figure 24: FlowChart Hierarchical Block 'Set and Initialize Attributes'

The flowchart above represents the first hierarchical block where the initial settings for the driver's journey are established. The process begins by setting the start time for the driver, utilizing data retrieved from an external database. This ensures that the driver's schedule aligns with planned routes and timing requirements predefined in the system.

Following the setting of the start time, the pickup and dropoff links for the driver's journey are determined. These links are also retrieved from the external database, specifying the exact locations where riders will be picked up and dropped off.

Once the start time and links are set, the start time is applied, allowing drivers to enter the system at the precise time instant necessary for their schedules.

Additionally, several driver attributes are initialized at this stage. Attributes such as 'pickup', 'dropoff', and 'exit' are set to zero, preparing the system to update these values as the driver progresses through their route.

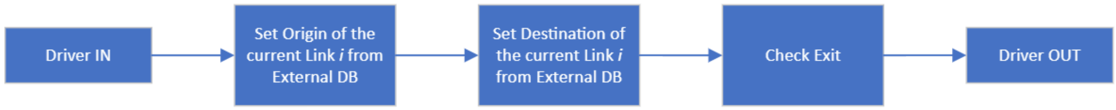


Figure 25: FlowChart Hierarchical Block 'Set Origin and Destination'

The segment of the flowchart above focuses on setting the origin and destination for the current link in the driver's route. These geographical points are retrieved from an external database, ensuring that each segment of the journey is defined by precise data. This step is necessary for accurately mapping the driver's immediate route.

After setting the origin and destination for the current link, the flowchart introduces a decision point involving the 'Exit' attribute. This attribute assesses whether the link just traveled by the driver was the last required link in their path for the day. If the 'Exit' attribute is set to one, it indicates that the driver has completed all assigned links, and thus, the driver proceeds towards the Drivers Exit, signaling the end of their duties for the day.

If, however, the 'Exit' attribute is not set to one, this implies there are further links to travel. Consequently, the driver continues on to the next link in their route. This mechanism ensures that the driver systematically completes all required segments of their journey, adhering to the planned route and schedule.

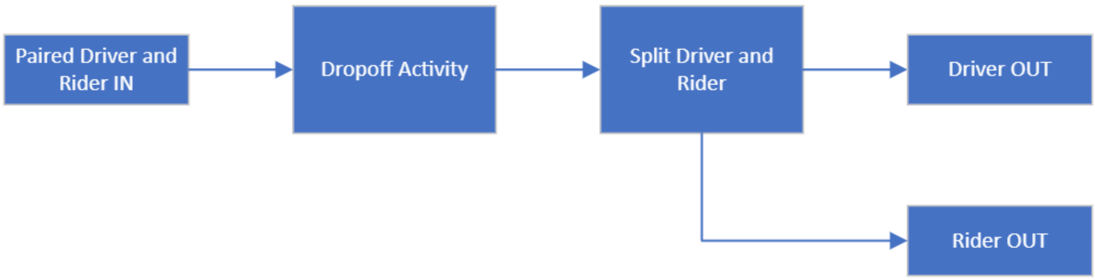


Figure 26: FlowChart Hierarchical Block 'Dropoff Model'

The flowchart above captures the steps involved in the dropoff process within the carpooling model. The sequence begins when a paired driver and rider enter the system at the predetermined dropoff link. At this stage, the dropoff activity is executed, which involves the rider being disembarked at their desired destination.

Following the completion of the dropoff activity, the driver and rider are separated. The driver proceeds along their path, continuing to fulfill any remaining travel segments. Meanwhile, the rider exits the system, having reached the endpoint of their journey.

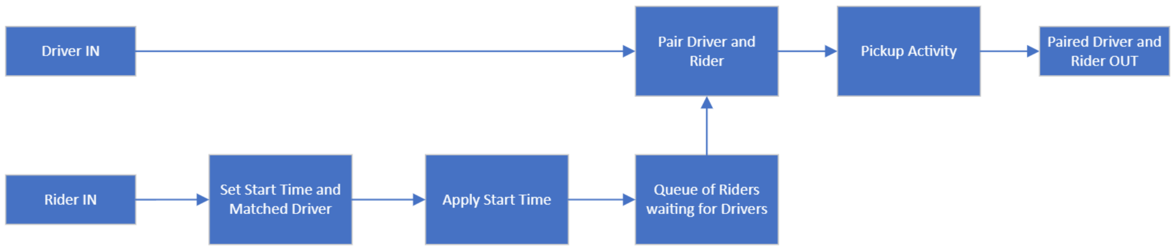


Figure 27: FlowChart Hierarchical Block 'Pickup Model'

The flowchart segment above represents the pickup model, detailing the process where drivers and riders are coordinated for successful pickups. Initially, both the driver and the rider enter the pickup model separately.

For the rider, the process starts with the setting of key attributes, which are retrieved from an external database. These attributes include the rider's start time and the identification of the matched driver, crucial for synchronizing the pickup. Once these attributes are set, the start time is applied to ensure that each rider enters the system at the correct, predetermined time.

Subsequently, riders enter a waiting queue. This queue symbolizes the riders' waiting period for their respective drivers.

At the designated pickup link (the specific location where the rider awaits) the flowchart shows the arrival of the correct driver. Upon the driver's arrival, the pairing between the designated driver and the waiting rider is executed. This step completes the pickup process and the driver and rider continue their journey together.

3.3 Traffic Data Analysis and Parameters Calibration

This research relies on the collection and analysis of real traffic data to simulate and optimize carpooling routes effectively within an urban environment. The data used in this study is derived from Floating Car Data (FCD), which is instrumental in capturing dynamic traffic conditions over time and across varying geographies.

3.3.1 Traffic Data Collection and Analysis

Source of Data The FCD used in this research was procured from TomTom, a leader in navigation and mapping products. TomTom's extensive experience in traffic management and route optimization ensures that the data is both reliable and comprehensive, making it ideal for academic studies that require precision and a broad dataset.

Description of Data The dataset provided by TomTom covers the entire urban layout of Genoa, which is intricately mapped out using a network of polylines. Each polyline accurately represents a segment of the city's road network, and together, they comprise a comprehensive digital model of Genoa's streets. This geospatial representation is crucial for simulating traffic flow and assessing various routing strategies within the city.

The primary attribute of interest in this dataset is the travel time associated with each polyline, which reflects the duration a vehicle takes to traverse a particular street segment. Travel times are recorded on an hourly basis, offering a detailed view of traffic dynamics at different times of the day. For each hour of a selected week, distinct travel times are available, capturing the variability in traffic patterns caused by factors such as peak hours, roadworks, accidents, or typical daily fluctuations.

The dataset's granularity ensures that the simulation model developed in this research can operate with a high degree of accuracy. By analyzing the hourly variations in travel times, the model can predict optimal travel schedules and suggest efficient carpooling strategies tailored to specific times and routes, significantly enhancing the effectiveness of traffic management solutions proposed by this thesis.

This high-resolution temporal data not only provides insights into the regular operation of the city's traffic but also helps in identifying bottlenecks and areas where interventions could yield substantial improvements in traffic flow and overall transportation efficiency.

Data Collection Methodology TomTom employs a comprehensive suite of technologies to collect Floating Car Data (FCD), primarily leveraging its widespread integration with satellite navigation systems found in various vehicle brands. This widespread adoption allows TomTom to gather a large volume of data from a diverse array of vehicles, encompassing a broad spectrum of driving patterns and conditions.

The data collection process involves several key technologies and methods:

- **GPS Tracking**
  Most vehicles equipped with satellite navigation systems provide real-time GPS tracking data to TomTom. This data includes precise geolocation coordinates, speed, and direction of travel, which are essential for mapping the vehicle's movement across the city's road network.

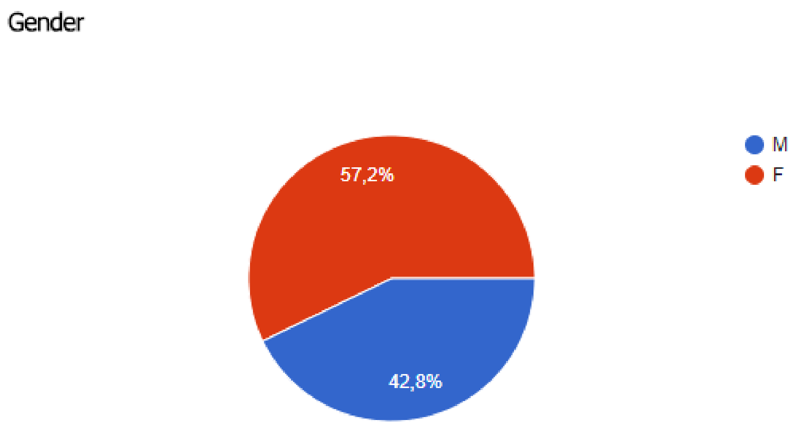
- **Mobile Applications**
  TomTom's mobile applications also play a crucial role in data collection. These apps, used by drivers in their daily commutes, gather extensive data including speed, location, and route choices, further enriching the dataset with detailed traffic insights from a user-based perspective.

Limitations and Challenges While FCD provides a wealth of information, there are inherent limitations to its use. The accuracy of the data can vary depending on the density of data points collected per area and the technology used. Additionally, the hourly resolution, while beneficial for observing larger trends, may not capture sudden changes in traffic conditions as effectively as more granular data would.

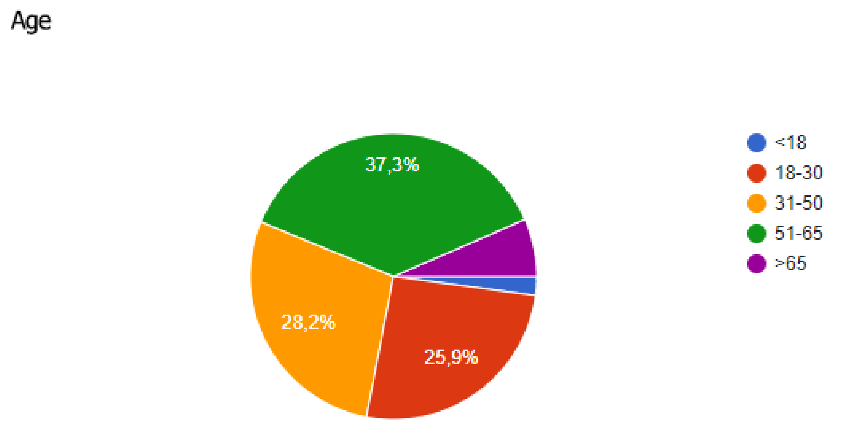
3.3.2 Survey-Based Parameters Calibration

In order to refine the parameters of a transportation model tailored for the network of the city of Genoa, a comprehensive survey was conducted, encompassing responses from 477 individuals. This section discusses the methodology employed in the survey, the demographic composition of the respondents, and the key findings that have significantly influenced the parameter settings of the model.

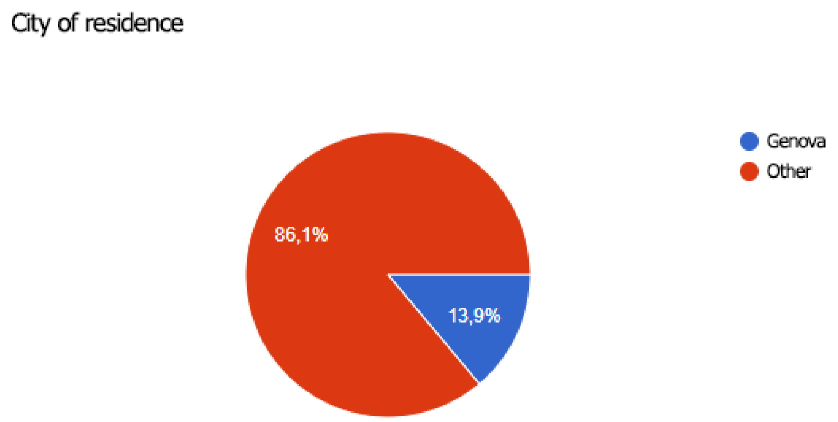
Demographic Overview The survey achieved a balanced gender representation, with 57% of respondents identifying as women.



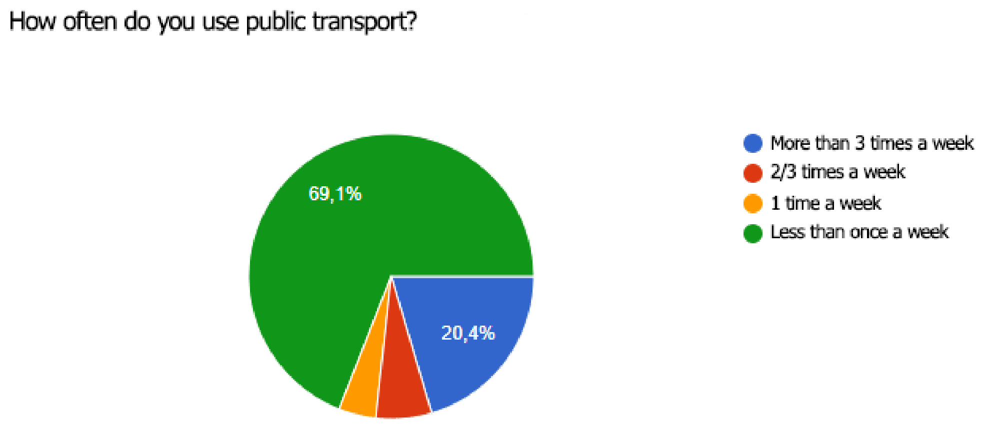
The age distribution among participants was well-rounded, with the majority falling within the 51-65 age range, followed closely by those aged 31-50 and 18-30.



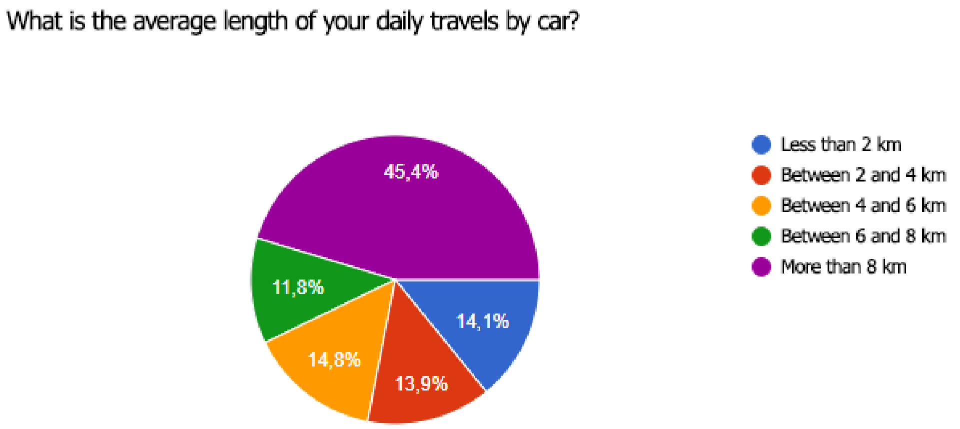
Notably, 14% of the respondents were residents of Genoa, providing crucial local insights into the city's transportation dynamics.



Transportation Preferences The predominant mode of transportation among the participants was private vehicles, with cars and motorbikes being the most popular choices. However, a significant minority (31%) reported using public transportation at least weekly.

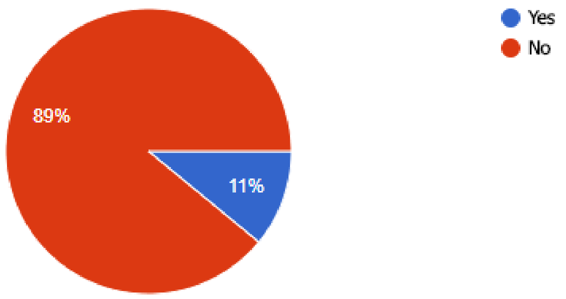


Approximately 45% of the respondents indicated that their daily travel exceeds 8 km.

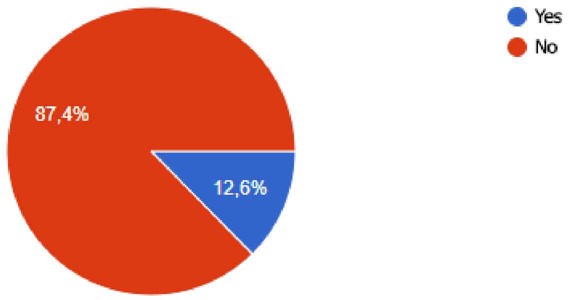


Interest in shared transportation services was modest, with 11% having used a Car Sharing service and 12.6% participating in Car Pooling.

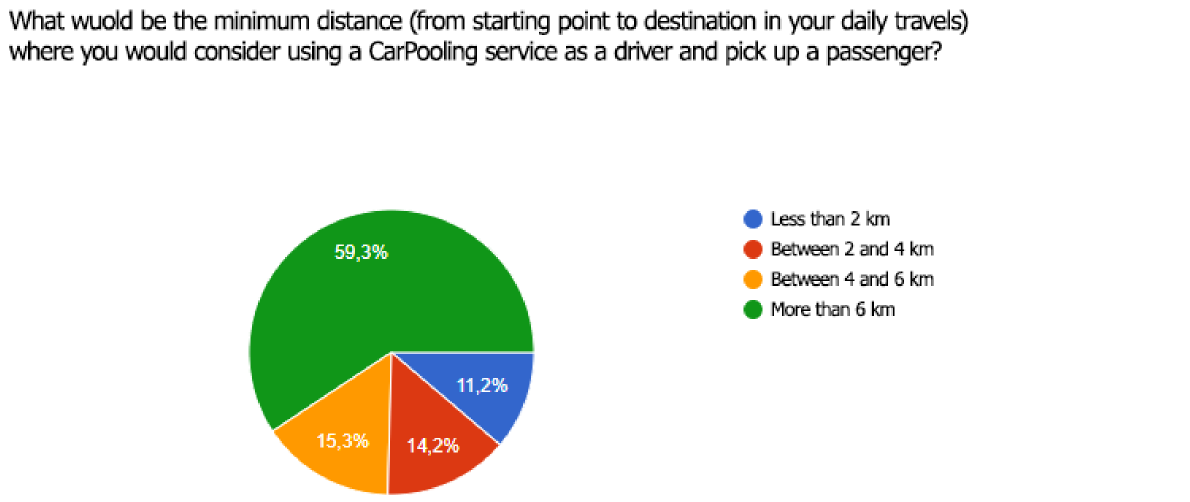
Have you ever used Car Sharing services? Car sharing means a very short-term car rental, the car can be taken and left soon after in the same spot or a different one within the city.



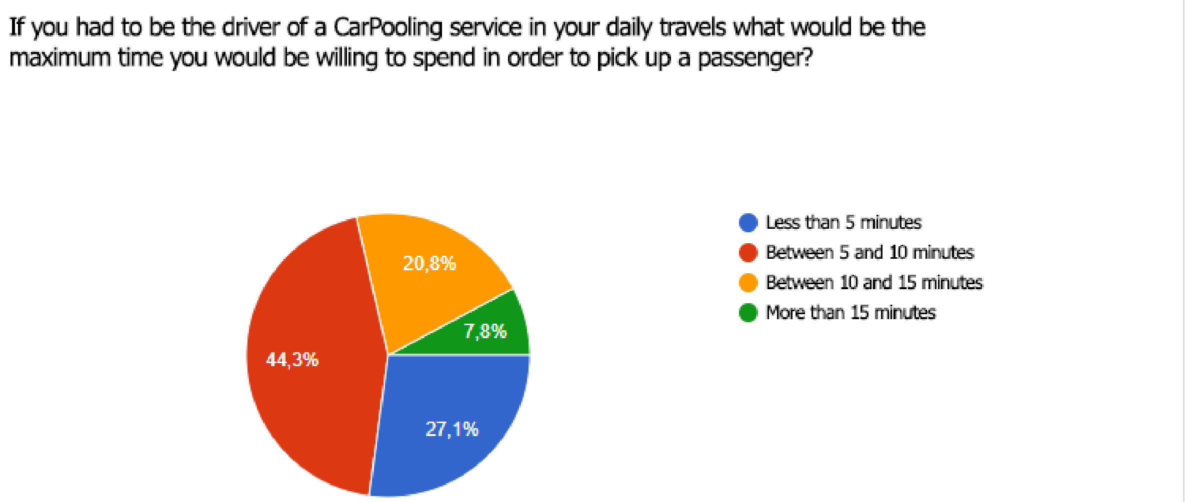
Have you ever used CarPooling services (e.g. BlaBLa Car)? CarPooling means sharing a ride with other passengers splitting the cost, organizing it through specific apps



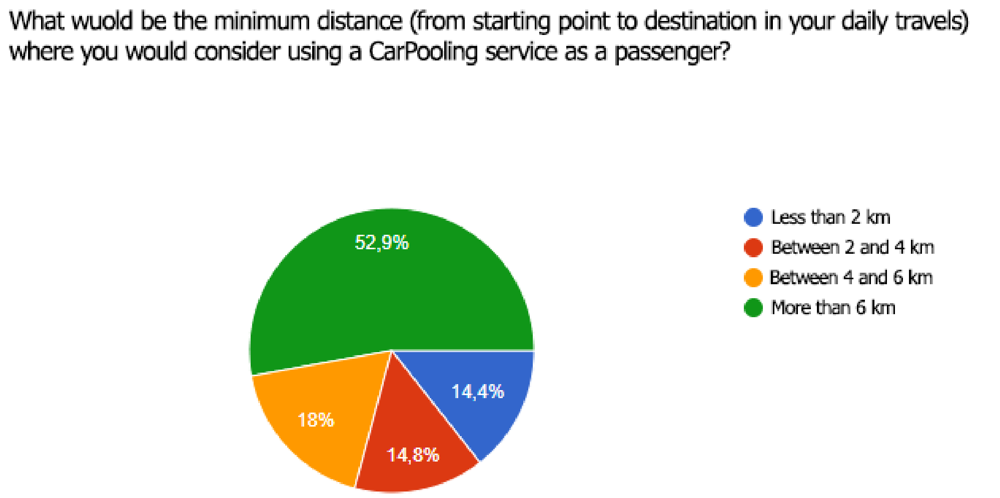
Drivers and Riders Preferences The survey included detailed questions about Car Pooling preferences, revealing that the majority would only consider sharing a ride for journeys longer than 6 km.



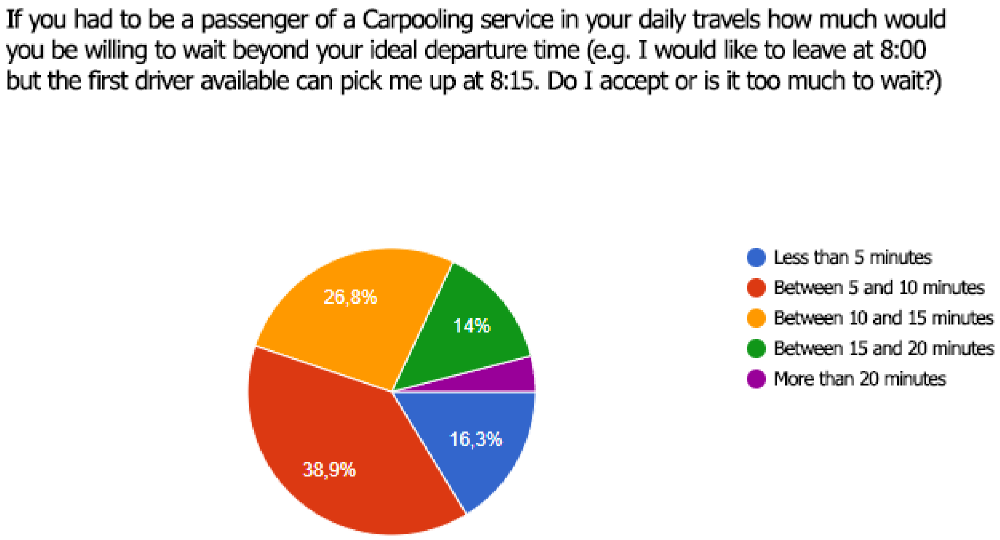
71% of the drivers were willing to deviate from their route by less than 10 minutes to pick up a rider.



From the perspective of potential riders, 53% would request a lift only for distances exceeding 6 km.

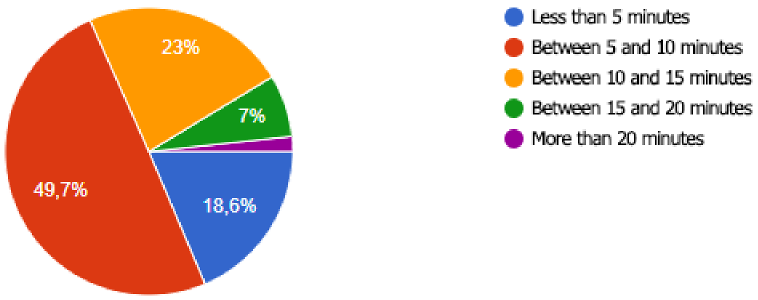


Timing flexibility was limited, with 55% of the respondents unwilling to alter their departure times by more than 10 minutes.



Additionally, 68% would tolerate a delay of no more than 10 minutes from the driver.

If you had to be a passenger of a CarPooling service in your daily travels what would be the maximum time you would wait a late driver after the established time?



Model Parameter Adjustments The survey findings directly influenced the calibration of several key parameters within the Genoa network model:

- **Minimum Travel Distance:** Both drivers and riders are modeled to prefer routes that are at least 6 km long, reflecting the survey's indication that shorter trips are less likely to involve carpooling.
- **Path Deviation:** Drivers are modeled to accept deviations from their planned route up to 30% longer than the original travel time, ensuring the model remains realistic in portraying driver behavior in potential carpooling scenarios.

4 Case Study

4.1 Description of the Study Area

The study area for the carpooling simulation model encompasses the Metropolitan City of Genoa. This city is known for its significant historical and economic importance as a major seaport, is characterized by its complex geography, featuring a rugged landscape with hills and narrow valleys leading down to the coast. This geographical setting deeply influences the urban layout and transportation dynamics, making it an intriguing area for studying transportation models.

The road network of Genoa includes a comprehensive mix of road types, from major highways to smaller urban and roads. The simulation model captures this diversity, incorporating all but the smallest alleyways and minor paths, which are excluded due to their limited impact on overall traffic flow. This detailed mapping ensures a thorough representation of the city's transportation infrastructure, allowing the model to simulate traffic conditions accurately.

The model utilizes travel time data for each network link, reflecting real traffic conditions during the specified time frame. By focusing on actual travel times rather than direct metrics like road capacity or traffic speeds, the simulation provides a realistic portrayal of traffic dynamics. This approach is particularly effective in understanding how carpooling can influence traffic patterns and commuter experiences in Genoa's varied road network.

4.2 Matching Algorithm

The matching algorithm I've developed in Python plays a critical role in integrating the Drivers and Riders Database for the simulation model. Initially, to model the road network of the city of Genoa, I created a graph in Python using a GeoJSON file which contained all nodes and links within the city's network. This file was imported into Python to construct a graph representing the road network. Additionally, travel times and lengths for all the links were imported from a CSV file and associated with their corresponding links in the graph. This preparation ensured that the graph in Python now accurately represents all the links and nodes of the Genoa city network, with each edge possessing associated attributes like length and travel time. This setup allows for operations such as computing the shortest paths based on travel times between two points.

The process of the simulation begins with the creation of profiles for 33 drivers and 100 riders, each assigned origins and destinations randomly selected from the nodes within the network.

In the following section, the algorithm for driver and rider matching is described step-by-step.

1. **Path Calculation:**
   For both drivers and riders, the algorithm computes the shortest path from their respective origins to their destinations based on the travel times of the links. This ensures that each has an optimal route based on the network's current conditions and layout.

2. **Deviation Computation**
   To match a driver with a rider, the algorithm calculates the possible deviation from the driver's original route to accommodate picking up and dropping off the rider. This deviation measures the additional travel time required to assist a rider as compared to the driver's standalone travel time.

3. **Deviation Constraint:**
   The algorithm ensures that this deviation does not exceed 30% of the driver's original travel time. This constraint is crucial to maintain efficiency and feasibility in the driver's schedule, preventing significant detours that could render the service impractical.

4. **Rider Assignment:**
   Among the potential matches, the rider that results in the minimum deviation for the driver is selected. This approach optimizes both the efficiency of the route and the convenience for the driver.

5. **Route Adjustment:**
   Once a rider is matched to a driver, the driver's route is updated to include this new passenger. The updated route consists of:

- Traveling from the driver's origin to the rider's origin.
- Proceeding from the rider's origin to the rider's destination.
- Completing the journey from the rider's destination back to the driver's original destination.

6. **Database Update:**
   Following the matching and route adjustments, the database is updated to reflect the matched pairs and their new routes. This matched database becomes a crucial element in the simulation, allowing for dynamic interaction and coordination between drivers and riders based on the optimized paths.

7. **Data Export:**
   Finally, the updated database of drivers and riders, along with the database containing the travel times and lengths of links, is exported.

4.3 Inputs of the Model

4.3.1 Travel Times Database

The foundation of the simulation is the Travel Times Database, which is constructed by refining the Floating Car Data (FCD) provided by TomTom. This data, which originally represents travel times over polylines, is manipulated to convert it into a graph form suitable for simulation. Each edge in the graph corresponds to a segment of the road network within Genoa, represented by a polyline in the FCD. For the purpose of this simulation, the key fields in this database are:

- **LinkID**
  Uniquely identifies each link in the network.
- **Origin**
  Represents the origin of the link, which is the starting point of the polyline.
- **Destination**
  Represents the destination of the link, which is the ending point of the polyline.
- **Travel Time**
  Specifies the travel time for the corresponding link, which varies by the hour of the day and day of the week to reflect real-world traffic conditions.
- **Length**
  Specifies the length for the corresponding link.

4.3.2 Drivers and Riders Database

The database used in the simulation model is a comprehensive resource that contains detailed information about both drivers and riders, including every node that composes each driver's path. This structured database is crucial as it provides the necessary information for setting up and running the simulation, ensuring that the attributes of drivers and riders in the model are accurately represented based on real-world data.

Within the database, there is extensive coverage of operational data for each participant, which includes their starting and ending points and their routes. Specifically for drivers, the database documents each node along their routes, offering detailed insights into the geographic coordinates.

This database is integral to the simulation model not only for initializing attributes at the start but also for influencing ongoing decisions within the model as the simulation runs.

By integrating this detailed database, the simulation model achieves a high level of accuracy and reliability, making it a powerful tool for testing hypotheses.

- **DriverID**
  A unique identifier for each driver.

- **Driver Origin**
  Represents the first point of the driver's path.
- **Driver Destination**
  Represents the final point of the driver's path.
- **Driver Start Time**
  Represents the time at which the driver starts from its origin.
- **RiderID**
  A unique identifier for each rider.
- **Rider Origin**
  Represent the starting point of the rider.
- **Rider Destination**
  Represent the final destination for the rider.
- **Rider Start Time**
  Represents the time at which the rider starts from its origin.
- **Rider Pickup Link**
  Identifies the link where the driver has to pick up the paired rider.
- **Rider Dropoff Link**
  Identifies the link where the driver has to drop off the paired rider.
- **Node 1, Node 2, etc.**
  Sequential nodes along the driver's path, indicating the route taken, including the deviation to pick up and drop off the rider.

4.4 Assumptions

In developing the carpooling simulation model for the city of Genoa, several foundational assumptions were made to ensure the accuracy and relevance of the model's outcomes. The simulation was designed to represent a one-hour period, specifically from 8:00 a.m. to 9:00 a.m. on a typical Monday morning, using Floating Car Data (FCD) from February 20, 2023. This particular timeframe was selected to capture typical morning rush hour conditions, allowing the model to incorporate real traffic data and thus, account for network congestion inherently. To address the variability in travel times, which is crucial for simulating real-world driving conditions, the model introduces a stochastic component. Travel times in the simulation follow a normal distribution centered around the observed real travel times, with a variance that acknowledges this unpredictability, enhancing the model's robustness and reliability.

Moreover, the simulation assumes a ratio of 3:1 between potential riders and drivers, totaling 100 riders and 33 drivers for the duration of the simulation. This ratio reflects a realistic scenario where riders significantly outnumber drivers, complicating the matching process but also providing a more comprehensive view of the demand and supply dynamics.

Another key assumption is that each driver can pick up only one rider during the simulation hour. This constraint is based on the urban setting of the model and the typically short duration of trips within city limits, where it would be impractical and less efficient for a driver to pick up multiple riders. This assumption helps to streamline the simulation process and makes the scenario more manageable and realistic, reflecting typical urban carpooling conditions where rides are brief and routes are direct.

4.5 Model Development

In this section of the thesis, we explore the discrete event simulation model developed using ExtendSim software, emphasizing its general applicability and scalability across various types of networks, ranging from small neighborhoods to entire regions. This flexibility is a cornerstone of the model's design, allowing it to be effectively implemented in diverse settings without the need for extensive customization.

The core idea behind the creation of the model is to avoid physically modeling an entire network, which can be both complex and resource-intensive. Instead, the model focuses on simulating individual network links. This approach simplifies the modeling process and enhances the model's adaptability. Each driver within the simulation is assigned an attribute that includes the 'linkID' of the link they are traveling on. This attribute is crucial as it ties each driver to a specific part of the network, thereby individualizing their experience within the simulation.

The travel times for these links are not hardcoded into the model but are instead dynamically retrieved from an external database. For the purpose of this thesis, the database was constructed using the network layout of the city of Genoa, supplemented with Floating Car Data (FCD) pertaining to this network. This method of integrating real-world data ensures that the simulation reflects current traffic conditions as closely as possible, enhancing the accuracy and reliability of the model outcomes.

A significant advantage of this modeling approach is that it allows for the simultaneous processing of multiple drivers. Since the model is designed to handle discrete events, each driver (represented as an item in ExtendSim) navigates through their designated link independently. The software's capability to process an infinite number of items concurrently means that each driver's travel time, specific to their current link, directly determines the duration of their activity within the model. This not only improves the efficiency of the simulation but also ensures that the model can scale to accommodate networks of varying sizes and complexities without degradation in performance.

By focusing on individual links and leveraging external data for real-time parameters, this ExtendSim model provides a robust framework for analyzing traffic dynamics and transportation strategies across diverse urban and regional contexts. The scalability and flexibility of this approach make it an invaluable tool in the field of transportation modeling, capable of addressing the unique challenges posed by different network scales and configurations.

In the following section it's provided a detailed description of the model.

The following figure shows the first part of the model, which includes the creation of the drivers and the hierarchical block where the attributes are set and initialized. Then there is a 'select item in' block, which collects the drivers that have already travelled at least one link and need to travel another link. So for every link in a driver's path, the driver at the end of the model is sent back to the beginning to start his next link. Then there is the hierarchical block where the origin and destination are set. Then there is a 'select item out' block, where the 'Exit' attribute of the driver is checked. If the value of the attribute is equal to 1, it means that it's the last link in the driver's path, so the driver is sent towards the 'Drivers Exit'.

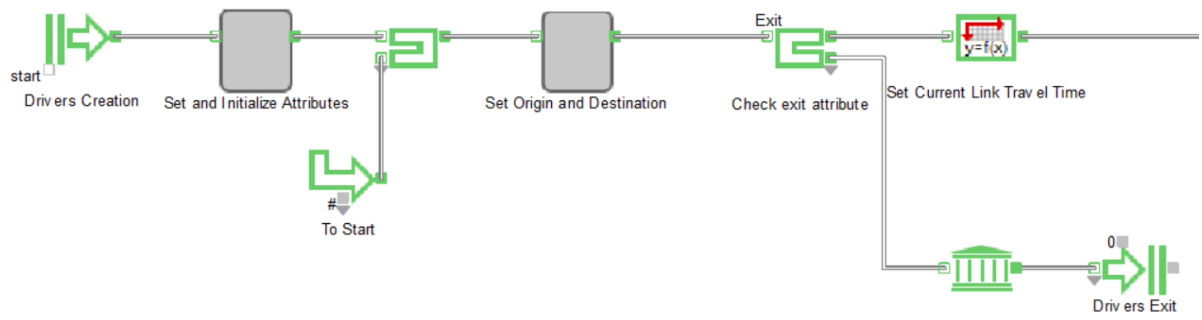


Figure 28: ExtendSim Model Part 1

The following figure represents the second part of the model, in which are present the pickup and dropoff models. First a check is done to verify if the driver has to pick up or drop off a rider during the link he is travelling on. If the 'Dropoff' attribute is equal to 1, it means that the driver has to drop off a rider and it enters the Dropoff Model hierarchical block. At the exit of this block, the driver procedes his travel, whrereas the rider is sent towards the 'Riders Exit'. Then if the 'Pickup' attribute is equal to 1, the driver has to pick up a rider, so it enters the Pickup Model hierarchical block.

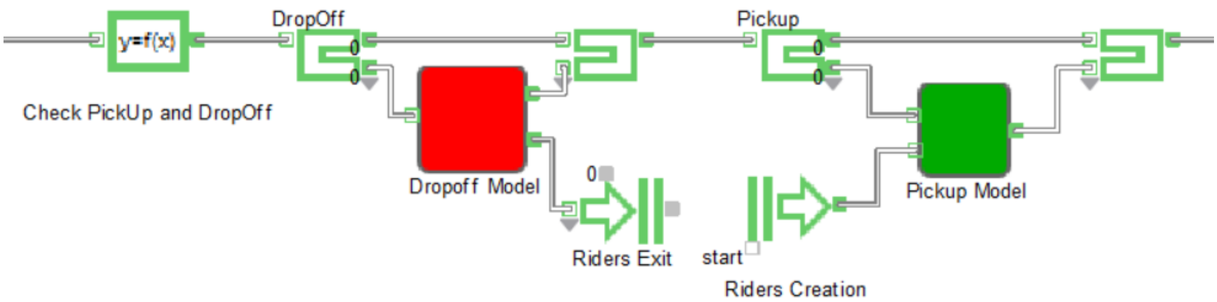


Figure 29: ExtendSim Model Part 2

The figure presented below illustrates the third and last part of the model, which includes the actual travel of the driver on the link. Before the travel activity, a stochastic travel time variation is applied to the travel time of the driver for that link. This variation is executed by adding to the original travel time a random value with a normal distribution with mean equal to zero and a standard deviation equal to 0,1. Then the rider is sent back to the start of the model, where it's checked if this was its last link. If it was his last link, it's sent towards the 'Drivers Exit', otherwise it's sent back into the model to travel his next link.

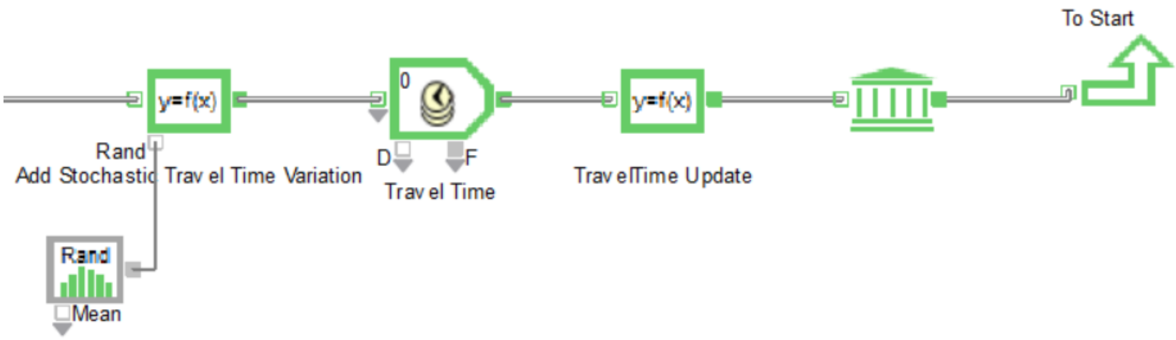


Figure 30: ExtendSim Model Part 3

In the following sections all the hierarchical blocks present in the model will be illustrated in detail.
In the figure below it's depicted the first hierarchical block of the model, which is the 'Set and Initialize Attributes' hierarchical block. In this block there are two query equations that set the 'StartTime', 'PickupLink' and 'DropoffLink' attributes of the drivers, extracting the data from external databases. Then there is the 'Apply Start Time' activity, which contains the drivers until their start time. In this way the start time is not to be set manually in the 'Create Drivers' block, but can be read from and external database. Once the start time is reached, the drivers exit from the acitvty and reach a set block, which initializes 'NumNode', 'LinkTravelTime' and 'Exit' to zero. The attribute NumNode is referred to the current node at which the driver is and it's used to set the origin and destination for each link of the driver's path.

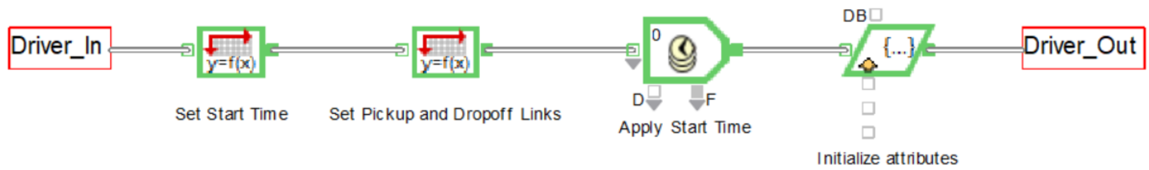


Figure 31: Set and Initialize Attributes Hierarchical Block

In the following figure it's represented the 'Set Origin and Destination' hierarchical block. When the driver enters this block, the origin of the current link is set, using the block 'Read' to take the information from and external database with all the nodes of the driver's paths. Then the attribute NumNode is increased by 1, in order to get the destination of the current link (that will then be the origin of the next link), using the same method as before, so reading it from and external database. Then there is an equation block that checks if the current link is the last link on the driver's path. If it's the last link, the 'Exit' attribute is set to 1 and the driver is sent towards the 'Drivers Exit'.

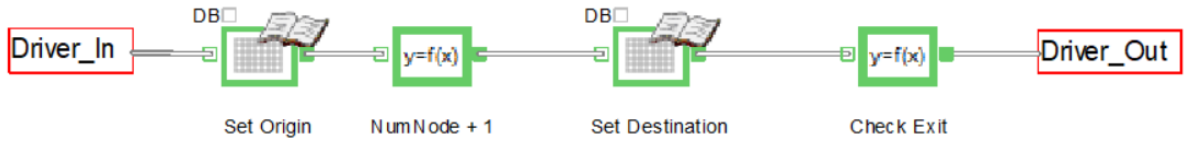


Figure 32: Set Origin and Destination Hierarchical Block

The following figure illustrates the 'Dropoff Model' hierarchical block. The paired driver and rider enter this block and the Dropoff activity is performed. After the activity, the rider is sent towards the exit of the hierarchical block, that is connected to the 'Riders Exit' and the driver is sent back into the model to procede with its travel.

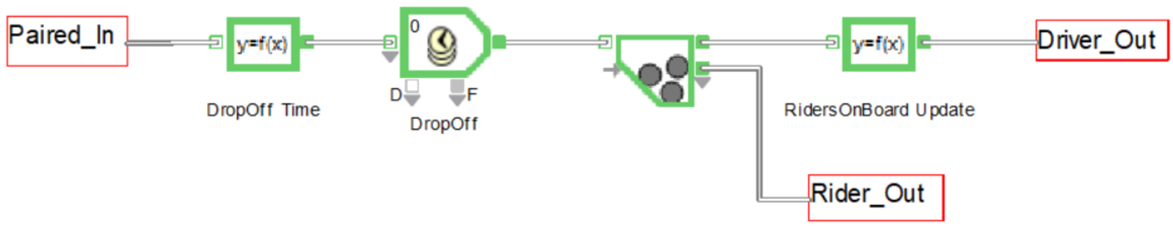


Figure 33: Dropoff Model Hierarchical Block

The following figure represents the 'Pickup Model' hierarchical block. In this block there are 2 input connectors, one for the drivers and one for the riders. The riders go trough a query equation block that sets their start time, taking the data from and external database. The following activity performs the delay that sets the right start time for the riders. After that, the riders enter a queue, which is governed by an equation. The rider is allowed to leave the queue only when its paired driver arrives in the following batch block, ensuring the correct pairing between riders and drivers. After the batch block, the pickup activity is performed and the driver and rider pair leaves the block.

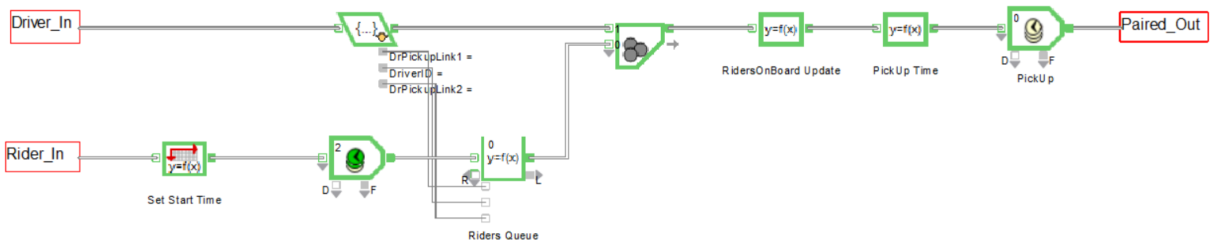


Figure 34: Pickup Model Hierarchical Block

4.6 Parameters and Variables

The carpooling simulation model for the Metropolitan City of Genoa utilizes ExtendSim software, which allows for a dynamic and interactive modeling environment. The main parameters of the model are defined as attributes that are attached to items within the simulation. These attributes are crucial as they not only uniquely identify elements but also govern the behavior of these elements throughout the simulation process. The flexibility to read and modify these attributes across different blocks of the model is fundamental, facilitating the control and direction of the simulation flow based on their values.

Here's a list of the key attributes in the simulation model:

- **DriverID:** This attribute uniquely identifies each driver in the simulation, ensuring that the data and actions related to each driver are accurately tracked and managed throughout the model.

- **DrStartTime:** Represents the start time for each driver. This parameter is pivotal for scheduling and synchronizing the movements and interactions of drivers within the simulated environment.

- **PickupLink:** Indicates the specific network link where a driver is scheduled to pick up a rider. This attribute directs the driver to the correct pickup location within the simulation's road network.

- **DropoffLink:** Similarly, this attribute specifies the link where the driver will drop off the rider, ensuring that each trip segment is completed as planned.

- **RiderID:** Uniquely identifies each rider in the simulation. This is essential for associating riders with their corresponding drivers and managing their journey details.

- **RiStartTime:** This attribute marks the start time for each rider, which is used to coordinate pickups and ensure timely interactions within the simulation.

- **Pickup:** A binary variable that controls whether a driver picks up a rider at a specific link. A value of 1 triggers the driver to enter the pickup phase of the model, performing the rider pickup.

- **Dropoff:** This binary variable indicates whether a driver is to drop off a rider at a given link. If set to 1, it directs the driver into the dropoff phase of the model, simulating the rider's disembarkation.

- **Exit:** Also a binary variable, indicating whether a driver has reached their destination. A value of 1 signifies that the driver can exit the simulation, marking the end of their participation.

5 Results

5.1 Driver Travel Time

In this section, we explore the results of our urban carpooling model simulation, focusing specifically on the total travel times for drivers from their origins to their destinations. The travel time for each driver includes also the deviation from their original routes to pick up and drop off the riders.

Our analysis is based on multiple simulation runs, each reflecting a unique scenario of traffic and carpooling dynamics.

Graphical representations in the form of line graphs will detail the travel times for each driver across the simulation runs, illustrating how travel times fluctuate with changes in traffic conditions.

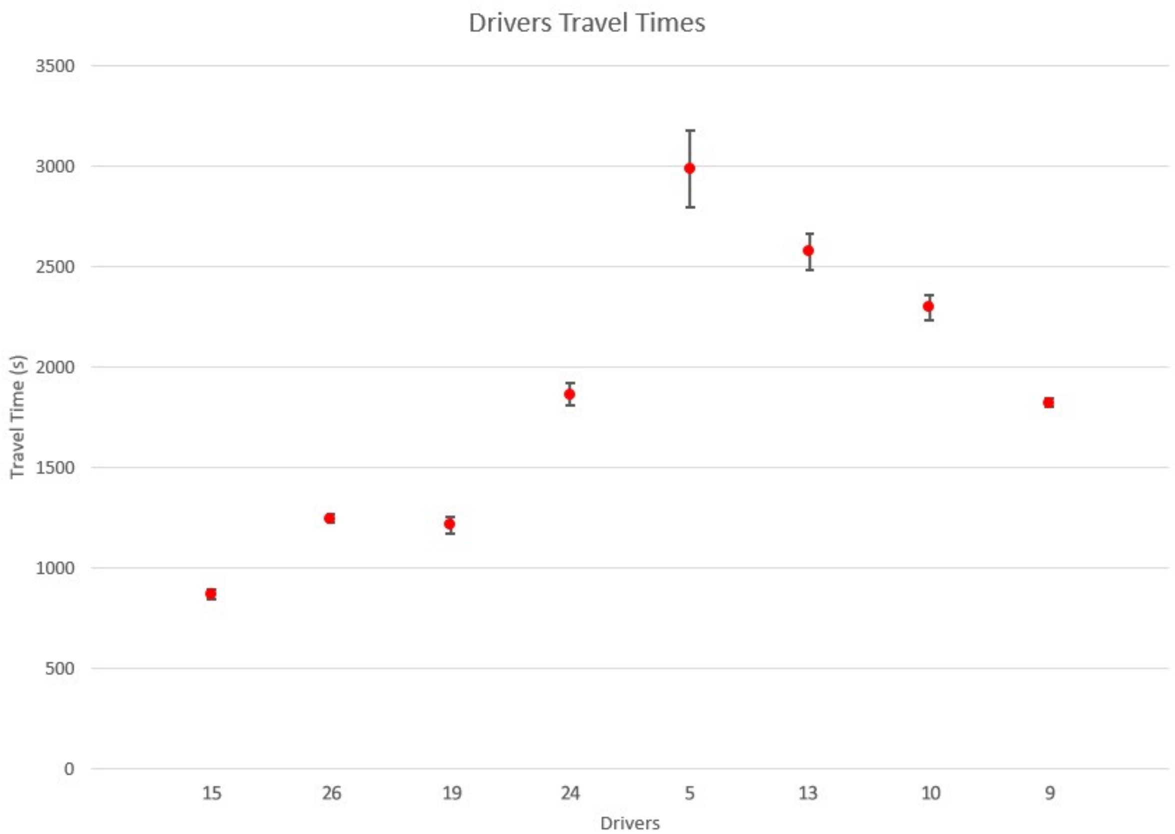


Figure 35: Drivers Travel Times

The graph above presents the travel times of individual drivers across multiple simulation runs in the city of Genoa. The x-axis categorizes the drivers, numbered according to their Driver ID. The y-axis displays the travel times, measured in seconds. The red dot represents the average travel time for a driver including all the simulation runs and the interval represents the confidence interval (95%).

The average driver travel time, considering all the drivers and all the simulations is 1860 seconds, corresponding to 31 minutes.

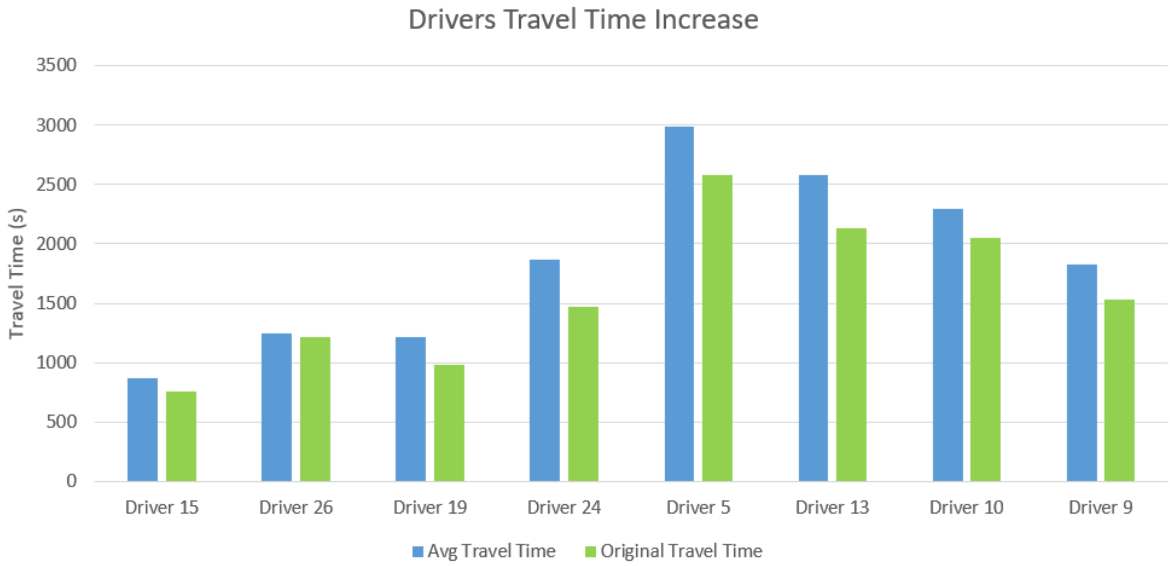


Figure 36: Drivers Travel Time Increase

The column graph above provides a comparative analysis of travel times for drivers involved in the urban carpooling simulation. Displayed on the x-axis are the individual drivers, each represented by two columns that depict distinct travel time scenarios. The orange column for each driver shows the shortest possible travel time from origin to destination without any deviations for carpooling activities, representing the optimal path under ideal conditions. In contrast, the blue column represents the average travel time across all simulation runs, taking into account the time added due to deviations for picking up and dropping off riders.

The graph demonstrates that the additional travel time incurred by carpooling does not exceed a 30% increase over the shortest travel time, adhering to the simulation's constraints. Furthermore, the results indicate an average increase in travel time of 16.9% across all drivers and simulation runs. It is important to note that this mean deviation could potentially be reduced if the number of riders and drivers in the system were to increase. With a more densely populated network, each driver would have a higher likelihood of being paired with riders who require shorter detours, optimizing the routing efficiency. This improved pairing logistics would not necessarily be about proximity but rather about minimizing the additional travel required. Consequently, an increase in system participants could effectively lower the mean deviation time by optimizing route deviations, thereby enhancing the overall efficiency and attractiveness of the carpooling system.

5.2 Rider Travel Time

In this section, we analyze the simulation results pertaining to the travel times of riders within the carpooling system in Genoa. Specifically, we analyze the travel times that represent the shortest path a rider would take from their point of origin to their destination.

Our analysis focuses on quantifying these shortest possible travel times and assessing their consistency across various simulation scenarios.

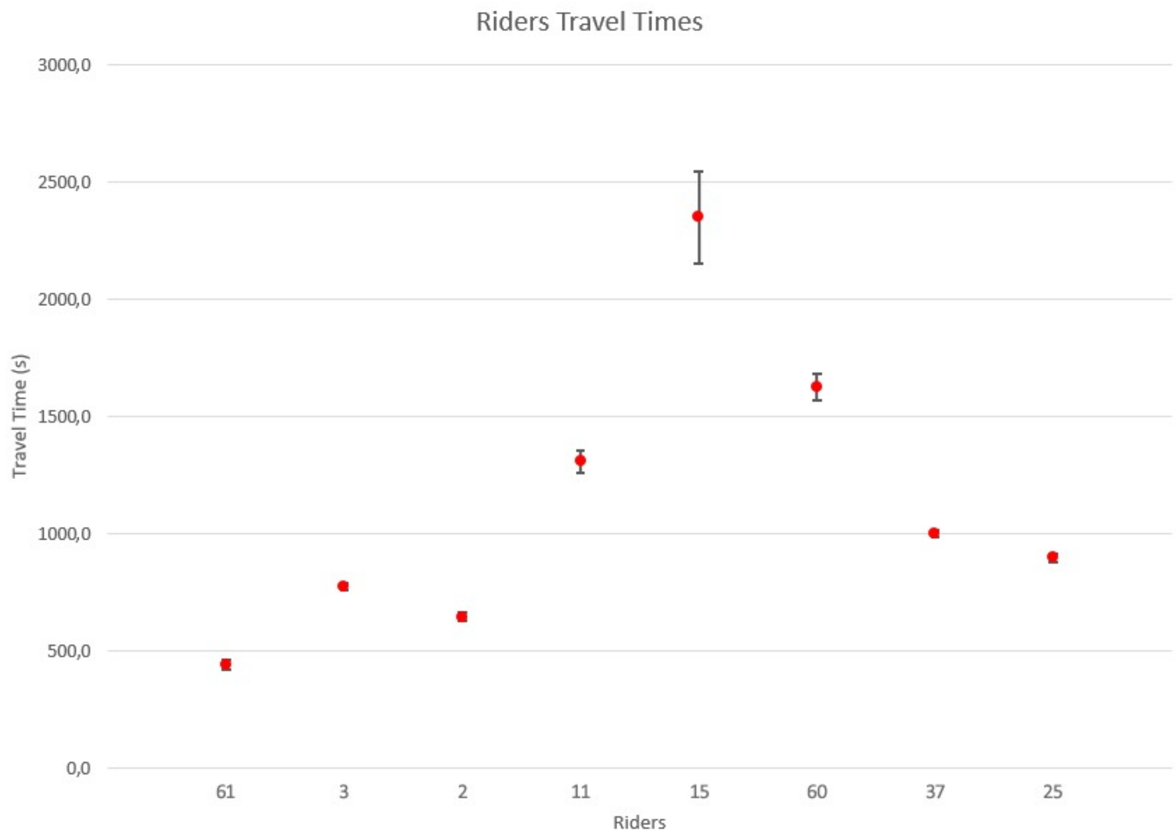


Figure 37: Riders Travel Times

The graph above presents the travel times of individual drivers across multiple simulation runs in the city of Genoa. The x-axis categorizes the drivers, numbered according to their Rider ID. The y-axis displays the travel times, measured in seconds. The red dot represents the average travel time for a rider including all the simulation runs and the interval represents the confidence interval (95%).

The average rider travel time, considering all the riders and all the simulations is 1131 seconds, corresponding to 18,85 minutes.

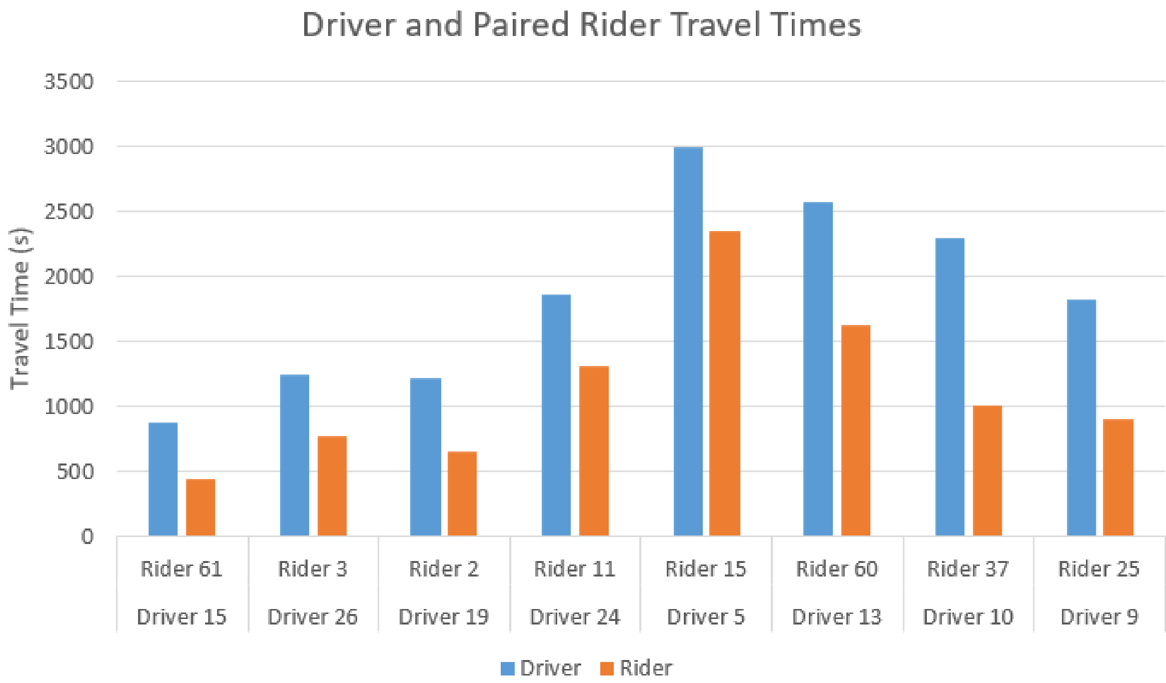


Figure 38: Driver and Paired Rider Travel Times

This column graph offers a comparative analysis of the travel times for paired drivers and riders within the urban carpooling system. The x-axis categorizes the various driver-rider couples identified throughout the simulation. Each pair is represented by two columns: the blue column indicates the travel time of the driver, while the orange column represents the travel time of the associated rider.

The average percentage of the travel that driver and rider do together, considering all the pairs of riders and drivers and all the simulation runs, is 59/

The graph reveals notable variations in the comparative travel times between drivers and riders. In some instances, the orange columns are significantly shorter than the corresponding blue columns, indicating that these riders have substantially shorter travel times compared to their drivers. This typically occurs when riders join partway through the driver's route and alight before the driver reaches their final destination. Conversely, other pairs show more similar heights in both columns, suggesting that these riders share a majority of the path with their drivers.

The differences between the travel times of the drivers and the paired riders are influenced by the minimum distances from their origins to their destinations. In this case study, the minimum distance for both the drivers and the riders is established at 6 km, based on survey results. This uniform minimum distance plays a critical role in matching dynamics. If, for instance, riders had a lower minimum distance from their origin to their destination compared to drivers, it would generally be easier to find suitable matches for these riders within the system. Such a scenario would likely result in more riders having shorter comparative travel times, as they could more frequently join routes that are already optimal or near-optimal for drivers, thereby minimizing additional travel time for both parties.

Furthermore, if the minimum travel distance required by drivers were consistently higher than that for riders, the percentage of the journey during which both driver and rider are together would be proportionately smaller. In such cases, it would be more efficient for a driver to pick up multiple riders throughout their route to maximize the utilization of their vehicle. However, in the context of this thesis, both drivers and riders have a high minimum travel distance of 6 km, making it nearly impossible for a driver to pick up more than one rider without significantly increasing their own travel time. This constraint affects the scalability of carpooling operations under the current model parameters and highlights an area for potential adjustment in future iterations of the simulation.

5.3 Rider Waiting Time

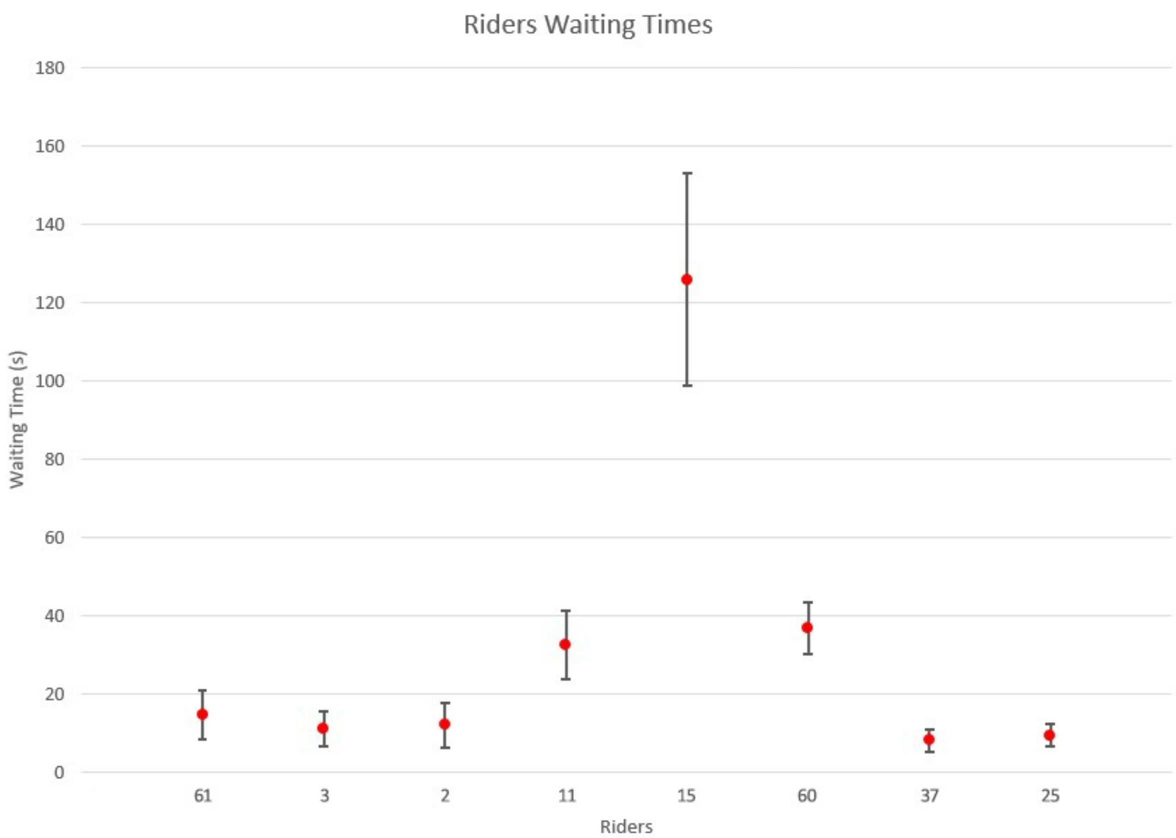


Figure 39: Riders Waiting Times

The graph above shows the average waiting time for all the riders. This parameter represents the average time that a rider has to wait for his driver. This waiting time represents a realistic result, because it takes into account the dynamic travel time variation for the links.

The average rider travel time, considering all the riders and all the simulations is 31 seconds.

5.4 Rider Travelled Distance and CO2 Saved

This section presents an analysis of the simulation results concerning the distance traveled by riders and the consequent CO2 savings achieved within the urban carpooling system. The focus of this analysis is to quantify the environmental benefits derived from adopting a shared travel model.

For each rider that opts into the carpooling system, the trip becomes a shared journey with a driver, meaning the rider does not contribute additional CO2 emissions from a separate vehicle. This directly translates to environmental benefits, which are quantified in this section. Each unit of CO2 saved reflects the positive impact of carpooling on urban air quality and contributes to broader sustainability goals.

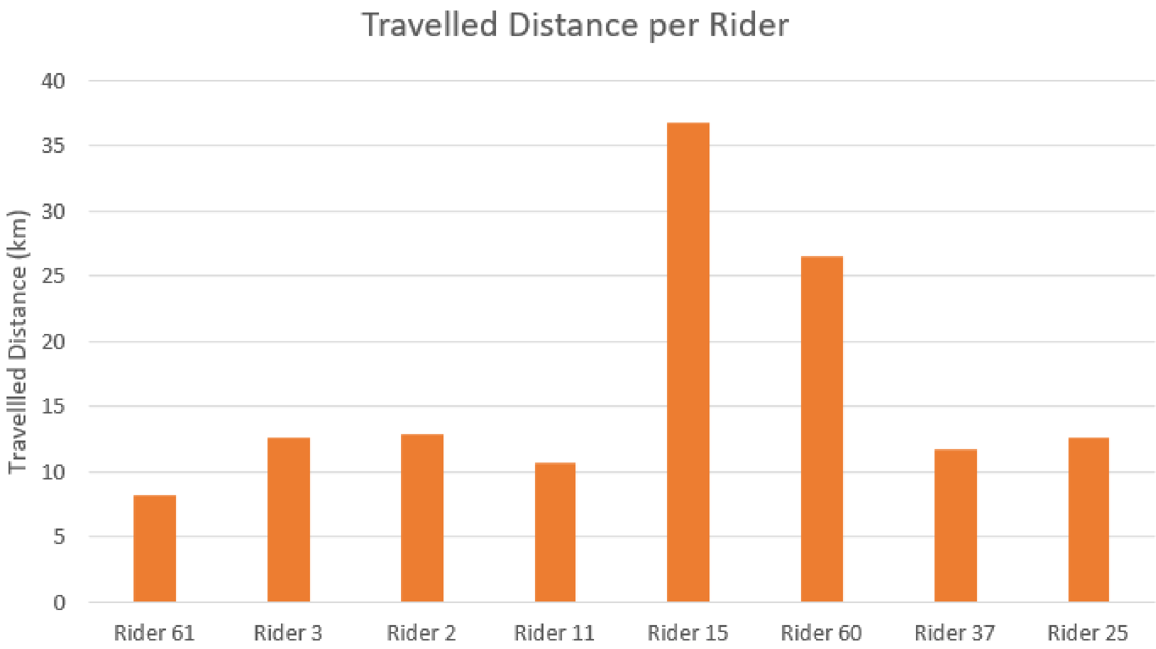


Figure 40: Travelled Distance per Rider

The graph above displays the distance traveled by each rider, plotted on a column chart where the x-axis represents individual riders and the y-axis measures the traveled distance in kilometers. Each column's height indicates the distance a rider has traveled from their origin to their destination, calculated using the shortest path in terms of travel time. The graph clearly shows a high variability in the length of the riders' paths, highlighting significant differences in journey lengths across the riders.

Importantly, every path represented on the graph is more than 6 km long, confirming that the constraints of the model are respected. This minimum distance constraint is critical in shaping the data displayed, as it sets a baseline for the shortest possible journey each rider can undertake within the simulation. As a result, the mean traveled distance for the riders in the model is 16.49 km. This average is significantly influenced by the imposed lower limit of 6 km, which ensures that all journeys are of a substantial length, thereby affecting the overall distribution and mean of the traveled distances.

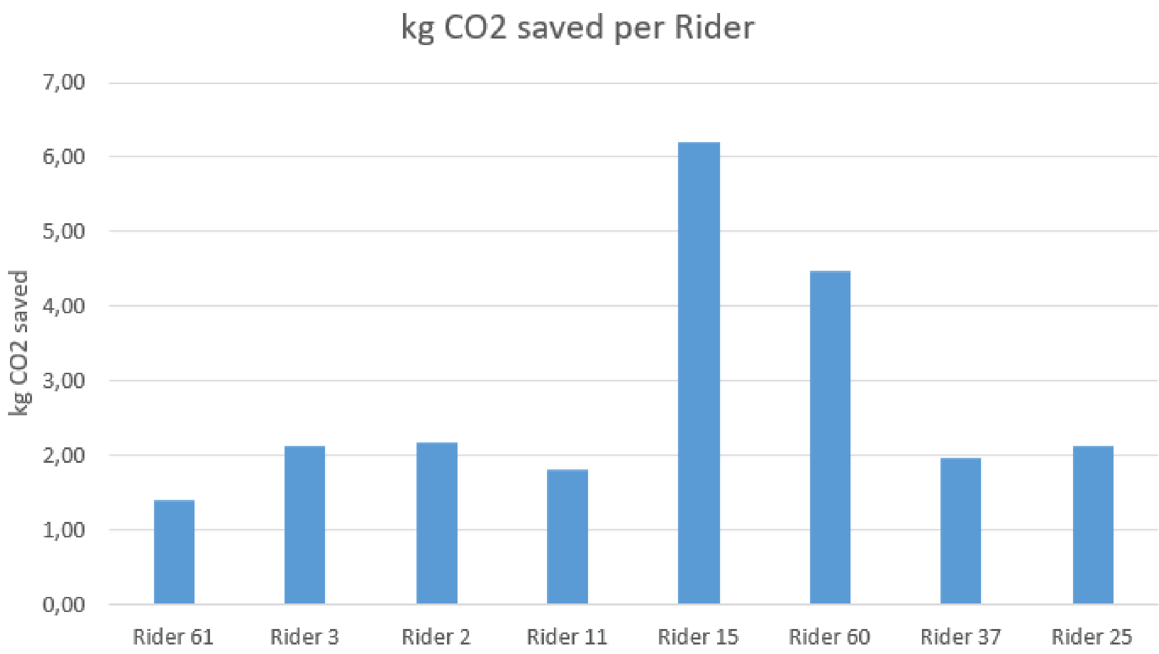


Figure 41: Kg of CO2 saved per Rider

This graph illustrates the CO2 savings for each rider within a simulation, depicted on a column chart where the x-axis labels each rider and the y-axis shows the amount of CO2 saved in kilograms. The savings are calculated based on the average CO2 emissions of Italian cars, which is 169 grams of CO2 per kilometer [8]. Each column represents the CO2 savings achieved by a rider, emphasizing the environmental impact of choosing alternative modes of transportation over typical car usage. The height of each column correlates directly to the amount of CO2 saved, offering a clear visual representation of the ecological benefits gained through each rider's journey in the simulation. Additionally, the mean CO2 saved per rider is 2.79 kg, further highlighting the overall effectiveness of the simulated transportation model in reducing carbon emissions.

To enhance the total CO2 savings across the carpooling system, there are two primary strategies that could be considered. The first approach involves increasing the minimum distance between riders' origins and destinations. This change would likely raise the mean traveled distance for each rider, thereby augmenting the CO2 savings per journey. However, a longer path could potentially reduce the matching rate, as finding suitable pairings for riders with extended routes becomes more challenging. This trade-off necessitates careful consideration of how distance adjustments might impact the overall efficiency of the carpooling system.

The second strategy focuses on reducing the journey distances for riders but increasing the number of riders a single driver can pick up during one trip. Although this would lower the mean CO2 savings per individual rider—since each rider's journey would be shorter—it could significantly increase the total number of riders served, thereby potentially raising the overall CO2 savings achieved by the system. This approach would require efficient route planning and scheduling to maximize the number of riders per vehicle without substantially extending the travel times of drivers.

Both strategies highlight the complexities and potential trade-offs involved in optimizing a carpooling system for greater environmental benefits. Balancing these factors is crucial for not only enhancing CO2 savings but also for maintaining or improving the service quality and user satisfaction within the carpooling system. By exploring these strategies, further research could identify optimal configurations that maximize both environmental benefits and operational efficiency.

5.5 Conclusions

This thesis has developed a discrete event simulation model that underscores its general applicability for analyzing urban carpooling systems across diverse geographic settings. Unlike traditional models that require detailed physical representations of road networks, this model employs a unique approach where a single virtual link dynamically assumes the characteristics of the required real-world link. This is achieved by reading attributes from drivers in transit and fetching corresponding travel times from an external database. Consequently, the model can adapt to any road network globally by merely updating the input database with the desired network data, without necessitating any structural modifications to the simulation framework itself.

Implemented specifically using the Metropolitan City of Genoa's road network for this study, the simulation represented the road network as a graph in Python, where travel times, sourced from Floating Car Data (FCD), were assigned as weights.

The python script populated this framework with entities representing drivers and riders. A matching algorithm minimized the deviation each driver needed to make from their optimal path to pick up a rider, with deviations capped at 30% of the travel time. Despite the flexibility and sophistication of this model, a critical limitation became apparent regarding the matching efficiency, which is highly dependent on the absolute numbers of drivers and riders. In the current simulation, the model included 100 riders and 33 drivers, maintaining a rider-to-driver ratio of 3:1. With this configuration, the percentage of riders who found a matched driver was only 8%. This low match rate can be attributed to the limited coverage of the network given the relatively small pool of participants.

The Metropolitan City of Genoa's road network, represented as a graph in the model, is extensive. The current number of riders and drivers only covers a fraction of this network. This partial coverage limits the opportunities for matching because many potential connections between riders and drivers are geographically unfeasible due to their sparse distribution across the network. By increasing the number of participants, it's likely that more areas of the network would have sufficient coverage, thereby enhancing the probability of matches.

Moreover, with a larger pool of drivers and riders, the dynamics of the matching algorithm could be better leveraged. The algorithm, designed to minimize deviations from the optimal paths up to 30% of travel time, currently operates under constraints that may not fully reflect the potential of a fully populated network. An increased participant pool would likely reduce the average deviation necessary for matches, as the choice set for each rider expands, allowing for more optimal pairings that require less deviation by the drivers.

Therefore, scaling up the number of participants not only addresses the coverage limitation but also enhances the operational efficiency of the matching algorithm. This adjustment would likely lead to a higher matching rate, making the system more attractive and efficient for users.

In conclusion, the discrete event simulation model designed in this thesis not only offers a scalable solution to urban carpooling challenges but also provides a robust platform for future research. Its ability to adapt to any urban network with minimal input adjustments makes it a powerful tool for urban planners and researchers aiming to optimize transportation systems worldwide.

5.6 Future Developments

5.6.1 Expansion to Other Urban Networks

The carpooling model developed in this thesis is designed to be universally applicable, maintaining the same parameters across different studies. The strength of the model lies in its adaptability to various urban networks without the need for recalibration of its core parameters. For application in new cities or regions, the only requirement is to update the input database to reflect the specific road network characteristics of the new area. This approach highlights the model's flexibility and potential for broader implementation in urban transportation planning without the need for extensive modifications.

5.6.2 Focused Localized Surveys

The initial model utilized survey data from participants across Italy, providing a broad basis for parameter estimation. However, to enhance the accuracy and relevance of the model specifically for Genoa or any other targeted city, conducting localized surveys would be valuable. This approach would refine the model's parameters to reflect the unique commuting patterns and preferences of the local population, potentially increasing the model's predictive accuracy and reliability.

5.6.3 Algorithm Optimization for Scalability

To test the resilience and efficiency of the carpooling system under different scales, it is crucial to optimize the existing Python matching algorithm. This optimization should aim at increasing the algorithm's ability to handle a larger number of users (both drivers and riders) efficiently, reducing computation times without sacrificing the quality of matchings.

5.6.4 Dynamic Rescheduling Capabilities

Integrating dynamic rescheduling capabilities into the carpooling application would allow drivers to adjust their routes in real-time, responding to changes in traffic conditions. This feature would not only improve the user experience by minimizing travel times but also enhance the system's overall efficiency.

5.6.5 Development of Backup Strategies

A significant enhancement for the carpooling application would be the introduction of backup strategies for riders unable to find immediate matches. One practical solution could be integrating alternative transportation options, such as taxis or shuttle services, within the application. This integration would ensure that these riders remain within the service ecosystem, improving customer satisfaction and retention. Strategic partnerships with local transportation providers could be a way to implement this feature, ensuring that alternative services are both timely and cost-effective.

A Appendices

In this chapter is described the python code developed for the matching algorithm.

A.1 Python Code

```
import  geopandas as gpd
import pandas as pd
import matplotlib.pyplot as plt
import networkx as nx
from shapely.geometry import Point
import plotly.graph_objects as go
import pandas as pd
import numpy
import random
from geopy.distance import geodesic
from datetime import datetime, timedelta, date

polylines = gpd.read_file("arcs.geojson")

# Create an empty graph
G = nx.Graph()

# Iterate over each polyline
for index, poly in polylines.iterrows():
    # Extract endpoints
    start_point = poly['geometry'].coords[0]
    end_point = poly['geometry'].coords[-1]
    poly_hash = poly['hash']  # Now using 'hash' as the identifier
       from GeoJSON
    poly_length = poly['Length']
    print(f"Hash: {poly['hash']}, Start Point: {poly.geometry.coords
       [0]}, End Point: {poly.geometry.coords[-1]}, Length: {poly['
       Length']}")

    # Add nodes
    G.add_node(start_point, pos=start_point)
    G.add_node(end_point, pos=end_point)

    # Add edge between the endpoints of the same polyline, include
       polyline hash as an attribute
    G.add_edge(start_point, end_point, hash=poly_hash, length=
       poly_length, travel_time=None)
```

```python
# Define the columns to load and their data types to optimize memory
    usage
cols_to_load = ['hash', 'utc_datetime', 'travel_time']
dtypes = {
    'hash': 'category',
    'utc_datetime': 'str',  # Could also use 'category' if the number
        of unique timestamps is low
    'travel_time': 'float'
}

# Load the CSV file with only the necessary columns and specified
    data types
travel_times = pd.read_csv("export.csv", usecols=cols_to_load, dtype=
    dtypes)

# Filter to only include data for a specific datetime, e.g.,
    '2023-02-20T08:00'
specific_time = '2023-02-20T08:00'
filtered_travel_times = travel_times[travel_times['utc_datetime'] ==
    specific_time]

# Check if filtered data is empty
if filtered_travel_times.empty:
    print("No data available for the specified time.")
else:
    print(f"Data loaded for {specific_time}. Proceeding with updates.
        ")

# Iterate over the filtered rows in the DataFrame to update the graph
for _, row in filtered_travel_times.iterrows():
    # Find the edges with this hash and update the travel time
    for (u, v, d) in G.edges(data=True):
        if d['hash'] == row['hash']:
            d['travel_time'] = row['travel_time']

# Create lists to memorize data while iterate through edges of the
    graph
hashes = []
start_nodes = []
end_nodes = []
lengths = []
traveltimes = []
```

```
# Iterate through edges of the graph
for (start, end, attributes) in G.edges(data=True):
    hashes.append(attributes['hash'])
    start_nodes.append(start)
    end_nodes.append(end)
    lengths.append(attributes['length'])
    traveltimes.append(attributes['travel_time'])


# Create DataFrame
links_travel_times = pd.DataFrame({
    'LinkID': hashes,
    'Origin': start_nodes,
    'Destination': end_nodes,
    'Length': lengths,
    'Travel Time': traveltimes

})

# Show DataFrame
print(links_travel_times)

# Function to convert tuple to string
def tuple_to_string(tup):
    return ','.join(map(str, tup))

# Create a new DataFrame 'links_travel_times_no_tuples' from '
   links_travel_times'
links_travel_times_no_tuples = links_travel_times.copy()

# Apply the function to convert tuples to strings in 'Origin' and '
   Destination' columns
links_travel_times_no_tuples['Origin'] = links_travel_times_no_tuples
   ['Origin'].apply(tuple_to_string)
links_travel_times_no_tuples['Destination'] =
   links_travel_times_no_tuples['Destination'].apply(tuple_to_string)

# Replace NaN values with 0 in 'Length' and 'Travel Time' columns
links_travel_times_no_tuples['Length'] = links_travel_times_no_tuples
   ['Length'].fillna(0).round().astype(int)
```

```
links_travel_times_no_tuples['Travel Time'] =
    links_travel_times_no_tuples['Travel Time'].fillna(0).round().
    astype(int)

# Display the new DataFrame
print(links_travel_times_no_tuples)

# Creating an integer mapping for each unique link hash in the order
    they appear
link_to_id = {hash_value: idx for idx, hash_value in enumerate(
    links_travel_times['LinkID'].unique(), start=1)}

# Applying the mapping to the original DataFrame to create a new
    column for the mapped IDs
links_travel_times['Mapped LinkID'] = links_travel_times['LinkID'].
    map(link_to_id)

# Extracting the mapping to a new DataFrame
Links_Mapping_df = links_travel_times[['LinkID', 'Mapped LinkID']].
    drop_duplicates().reset_index(drop=True)

# Display the Links Mapping DataFrame
print(Links_Mapping_df)

# Export the DataFrame to a CSV file
Links_Mapping_df.to_csv('Links_Mapping.csv', index=False)

# Create a mapping of each node tuple to a unique NodeID with the
    node formatted as a string
node_to_id = {','.join(map(str, node)): idx for idx, node in
    enumerate(G.nodes(), start=1)}

# Create a DataFrame from the mapping
nodes_mapping_df = pd.DataFrame(list(node_to_id.items()), columns=['
    Node', 'NodeID'])

# Display the DataFrame
print(nodes_mapping_df)

# Export the DataFrame to a CSV file
nodes_mapping_df.to_csv('Nodes_Mapping.csv', index=False)

# Calculate the number of nodes and edges
```

```python
num_nodes = G.number_of_nodes()
num_edges = G.number_of_edges()

print("Number of nodes:", num_nodes)
print("Number of edges:", num_edges)

# Assume G is your graph with nodes as coordinates
node_list = list(G.nodes())

def pick_random_locations(node_list, min_distance_km):
    while True:
        origin = random.choice(node_list)
        destination = random.choice(node_list)
        if geodesic(origin, destination).km >= min_distance_km:
            return origin, destination

# Generate data for each driver
data = []
fixed_date = "2023-01-01"  # Setting a fixed date
for driver_id in range(1, 34):  # Assuming 15 drivers
    origin, destination = pick_random_locations(node_list, 6)  # 6 km
        minimum distance
    start_minute = random.randint(0, 59)  # random minute between 0
       and 59
    start_time = f"{fixed_date} 08:{start_minute:02d}:00"  #
       formatted start time, e.g., "2023-01-01 08:05:00"

    data.append({
        'DriverID': driver_id,
        'Origin': origin,
        'Destination': destination,
        'StartTime': start_time
    })

# Create DataFrame
drivers_df = pd.DataFrame(data)

# Function to convert datetime string to datetime object
def convert_to_datetime(date_str):
    return datetime.strptime(date_str, '%Y-%m-%d %H:%M:%S')

# Applying the conversion
```

```python
drivers_df['StartTime'] = drivers_df['StartTime'].apply(
    convert_to_datetime)

# Display the DataFrame
print(drivers_df)

# List to hold data for the new dataset
drivers_paths = []

# Compute shortest path for each driver
for index, row in drivers_df.iterrows():
    try:
        shortest_path = nx.dijkstra_path(G, source=row['Origin'],
            target=row['Destination'], weight='travel_time')
        # Create a dictionary for each driver's path and append to
            the list
        path_dict = {'DriverID': row['DriverID']}
        for idx, node in enumerate(shortest_path):
             path_dict[f'Node {idx+1}'] = node
        drivers_paths.append(path_dict)
    except nx.NetworkXNoPath:
        print(f"No path exists between {row['Origin']} and {row['
            Destination']} for Driver {row['DriverID']}")
    except KeyError:
        print(f"One of the specified nodes does not exist in the
            graph for Driver {row['DriverID']}")

# Convert the list of dictionaries to a DataFrame for easier viewing
    and manipulation
drivers_paths_df = pd.DataFrame(drivers_paths)

# Display the new DataFrame
print(drivers_paths_df)

drivers_paths = []

for index, row in drivers_df.iterrows():
    origin = row['Origin']
    destination = row['Destination']

    try:
        # Retrieve the shortest path using Dijkstra's algorithm with
            'travel_time' as the edge weight
```

```
        shortest_path = nx.dijkstra_path(G, source=origin, target=
           destination, weight='travel_time')

        # Calculate total travel time by summing the 'travel_time' of
            the edges along the path
        total_travel_time = 0
        for i in range(len(shortest_path) - 1):
            total_travel_time += G[shortest_path[i]][shortest_path[i
               + 1]]['travel_time']

        # Create a dictionary for each driver's path and include
           total travel time
        path_dict = {'DriverID': row['DriverID'], 'TotalTravelTime':
           total_travel_time}
        for idx, node in enumerate(shortest_path):
            path_dict[f'Node {idx+1}'] = node
        drivers_paths.append(path_dict)

    except nx.NetworkXNoPath:
        print(f"No path exists between {origin} and {destination} for
            Driver {row['DriverID']}")
        drivers_paths.append({'DriverID': row['DriverID'], '
           TotalTravelTime': None})
    except KeyError as e:
        print(f"KeyError accessing edge data: {e}")

drivers_paths_df = pd.DataFrame(drivers_paths)

# Display the new DataFrame
print(drivers_paths_df)

node_list = list(G.nodes())

def pick_random_locations(node_list, min_distance_km):
    while True:
        origin = random.choice(node_list)
        destination = random.choice(node_list)
        while destination == origin:  # Ensure origin and destination
            are not the same
            destination = random.choice(node_list)
        if geodesic(origin, destination).km >= min_distance_km:
            return origin, destination
```

```
# Assuming you have a specific number of riders, say 100
num_riders = 100
riders_data = []
fixed_date = "2023-01-01"  # Setting a fixed date

node_list = list(G.nodes())  # List of all nodes in the graph

for rider_id in range(1, num_riders + 1):
    origin, destination = pick_random_locations(node_list, 6)  # 3 km
        minimum distance
    start_minute = random.randint(0, 59)  # random minute between 0
       and 59
    start_time = f"{fixed_date} 08:{start_minute:02d}:00"  #
       formatted start time, e.g., "2023-01-01 08:05:00"
    riders_data.append({
        'RiderID': rider_id,
        'Origin': origin,
        'Destination': destination,
        'StartTime': start_time
    })

# Create DataFrame
df_riders = pd.DataFrame(riders_data)

# Function to convert datetime string to datetime object
def convert_to_datetime(date_str):
    return datetime.strptime(date_str, '%Y-%m-%d %H:%M:%S')

# Applying the conversion
df_riders['StartTime'] = df_riders['StartTime'].apply(
   convert_to_datetime)


print(df_riders)

# List to hold data for the new dataset
riders_paths = []

# Compute shortest path for each driver
for index, row in df_riders.iterrows():
```

```
    try:
        shortest_path = nx.dijkstra_path(G, source=row['Origin'],
           target=row['Destination'], weight='travel_time')
        # Create a dictionary for each driver's path and append to
           the list
        path_dict = {'RiderID': row['RiderID']}
        for idx, node in enumerate(shortest_path):
            path_dict[f'Node {idx+1}'] = node
        riders_paths.append(path_dict)
    except nx.NetworkXNoPath:
        print(f"No path exists between {row['Origin']} and {row['
           Destination']} for Rider {row['RiderID']}")
    except KeyError:
        print(f"One of the specified nodes does not exist in the
           graph for Rider {row['RiderID']}")

# Convert the list of dictionaries to a DataFrame for easier viewing
   and manipulation
riders_paths_df = pd.DataFrame(riders_paths)

# Display the new DataFrame
print(riders_paths_df)

# Perform the merge including 'StartTime', 'Origin', and 'Destination
   '
riders_paths_df = riders_paths_df.merge(df_riders[['RiderID', '
   StartTime', 'Origin', 'Destination']], on='RiderID', how='left')

# Reorder the columns in the DataFrame
column_order = ['RiderID', 'StartTime', 'Origin', 'Destination'] + [
   col for col in riders_paths_df.columns if col not in ['RiderID', '
   StartTime', 'Origin', 'Destination']]
riders_paths_df = riders_paths_df[column_order]

# Display the updated DataFrame
print(riders_paths_df)

def calculate_deviation(driver_path, rider_origin, rider_destination,
    G, original_travel_time):
    min_additional_time = float('inf')
    best_insertion_index = -1
```

```
    # Calculate the travel time for the whole driver path without
       rider
    original_path_time = sum(
        nx.shortest_path_length(G, source=driver_path[i], target=
           driver_path[i+1], weight='travel_time')
        for i in range(len(driver_path) - 1)
    )

    # Calculate deviation considering rider pickup and drop-off
    for i in range(len(driver_path) - 1):
        path_to_origin = nx.shortest_path_length(G, source=
           driver_path[0], target=rider_origin, weight='travel_time')
        direct_path = nx.shortest_path_length(G, source=rider_origin,
            target=rider_destination, weight='travel_time')
        path_from_destination = nx.shortest_path_length(G, source=
           rider_destination, target=driver_path[-1], weight='
           travel_time')

        new_total_time = path_to_origin + direct_path +
           path_from_destination

        print(f"Deviation at insertion between {driver_path[i]} and {
           driver_path[i+1]}: New Total Time {new_total_time}, Limit
           {original_path_time * 1.2}, Path to Origin {path_to_origin
           }, Direct Path {direct_path}, Path From Destination {
           path_from_destination}, Original Path Time {
           original_path_time}")

        if new_total_time <= original_path_time * 1.3 and
           new_total_time < min_additional_time:
            min_additional_time = new_total_time
            best_insertion_index = i

    return min_additional_time, best_insertion_index

def pair_riders_with_drivers(riders_df, drivers_df, G):
    matches = []
    driver_rider_count = {driver_id: 0 for driver_id in drivers_df['
       DriverID']}

    for _, rider in riders_df.iterrows():
        best_driver = None
        minimal_additional_time = float('inf')
```

```
        for _, driver in drivers_df.iterrows():
            if driver_rider_count[driver['DriverID']] >= 1:
                continue  # Skip if the driver already has 1 rider

            original_travel_time = driver['TotalTravelTime']
            driver_path = [node for idx, node in driver.items() if
                idx.startswith('Node') and pd.notna(node)]
            additional_time, insertion_idx = calculate_deviation(
                driver_path, rider['Origin'], rider['Destination'], G,
                 original_travel_time)

            # Update the minimal additional time without considering
                wait time
            if additional_time < minimal_additional_time:
                minimal_additional_time = additional_time
                best_driver = driver['DriverID']

        # Add the match if a suitable driver has been found
        if best_driver:
            matches.append({
                'RiderID': rider['RiderID'],
                'DriverID': best_driver,
                'TotalDriverTravelTime': minimal_additional_time
            })
            driver_rider_count[best_driver] += 1

    return pd.DataFrame(matches)

matched_riders_drivers_df = pair_riders_with_drivers(df_riders,
    drivers_paths_df, G)
print(matched_riders_drivers_df)

# Function to calculate the new driver path
def calculate_new_driver_path(driver_id, driver_origin, rider_origin,
    rider_destination, driver_destination, G):
    # Calculate paths using tuples for graph nodes
    path_to_rider_origin = nx.dijkstra_path(G, source=driver_origin,
        target=rider_origin, weight='travel_time')
    path_rider_origin_to_destination = nx.dijkstra_path(G, source=
        rider_origin, target=rider_destination, weight='travel_time')
    path_from_rider_destination = nx.dijkstra_path(G, source=
        rider_destination, target=driver_destination, weight='
```

```
        travel_time')

    # Combine paths
    full_path = path_to_rider_origin[:-1] +
        path_rider_origin_to_destination[:-1] +
        path_from_rider_destination

    # Get the 'hash' for the pickup and dropoff links
    pickup_link = G[path_rider_origin_to_destination[0]][
        path_rider_origin_to_destination[1]]['hash']
    dropoff_link = G[path_rider_origin_to_destination[-2]][
        path_rider_origin_to_destination[-1]]['hash']

    # Convert tuple coordinates to string before logging or storing
    driver_origin_str = ','.join(map(str, driver_origin))
    rider_origin_str = ','.join(map(str, rider_origin))
    rider_destination_str = ','.join(map(str, rider_destination))
    driver_destination_str = ','.join(map(str, driver_destination))

    # Prepare the data for output
    result = {
        'DriverID': driver_id,
        'Pickup Link': pickup_link,
        'Dropoff Link': dropoff_link,
        'Driver Origin': driver_origin_str,
        'Rider Origin': rider_origin_str,
        'Rider Destination': rider_destination_str,
        'Driver Destination': driver_destination_str
    }

    # Add each node in the path as a separate entry in the result
        dictionary
    for i, node in enumerate(full_path):
        result[f'Node {i+1}'] = ','.join(map(str, node))

    return result
# Assuming 'matched_riders_drivers_df' contains the matches with
    additional time calculations
new_paths = []
for index, match in matched_riders_drivers_df.iterrows():
    driver_id = match['DriverID']
    rider_id = match['RiderID']
```

```
    # Retrieve driver and rider details
    driver_details = drivers_df[drivers_df['DriverID'] == driver_id].
       iloc[0]
    rider_details = riders_paths_df[riders_paths_df['RiderID'] ==
       rider_id].iloc[0]

    # Calculate new path considering the deviation to pick up the
       rider
    new_path_info = calculate_new_driver_path(
        driver_id,
        driver_details['Origin'],
        rider_details['Origin'],
        rider_details['Destination'],
        driver_details['Destination'],
        G
    )

    # Include the 'DriverStartTime', 'RiderStartTime' and 'RiderID'
       from the driver's original schedule and matched data
    new_path_info['DriverStartTime'] = driver_details['StartTime']
    new_path_info['RiderStartTime'] = rider_details['StartTime']
    new_path_info['RiderID'] = rider_id
    new_paths.append(new_path_info)

# Create the DataFrame from the new paths list
final_paths_df = pd.DataFrame(new_paths)

# Reorder columns to place 'DriverStartTime' as the second column
cols = ['DriverID', 'DriverStartTime'] + [col for col in
   final_paths_df.columns if col not in ['DriverID', 'DriverStartTime
   ']]
final_paths_df = final_paths_df[cols]

# Convert 'DriverStartTime' to datetime if not already
final_paths_df['DriverStartTime'] = pd.to_datetime(final_paths_df['
   DriverStartTime'])

# Convert 'RiderStartTime' to datetime if not already
final_paths_df['RiderStartTime'] = pd.to_datetime(final_paths_df['
   RiderStartTime'])

# Extract minutes and create a new column
```

```python
final_paths_df['DriverStartTimeMin'] = final_paths_df['
    DriverStartTime'].dt.minute

# Extract minutes and create a new column
final_paths_df['RiderStartTimeMin'] = final_paths_df['RiderStartTime'
    ].dt.minute

# Convert 'DriverID' to integer
final_paths_df['DriverID'] = final_paths_df['DriverID'].astype(int)

# Convert 'RiderID' to integer
final_paths_df['RiderID'] = final_paths_df['RiderID'].astype(int)

# Define the desired order for columns, placing 'StartTimeMinutes' as
     the third column
column_order = ['DriverID', 'DriverStartTime', 'DriverStartTimeMin',
    'RiderID', 'RiderStartTime', 'RiderStartTimeMin'] + [col for col
    in final_paths_df.columns if col not in ['DriverID', '
    DriverStartTime', 'DriverStartTimeMin', 'RiderID', 'RiderStartTime
    ', 'RiderStartTimeMin']]

# Reorder the DataFrame columns
final_paths_df = final_paths_df[column_order]

# Display the new DataFrame
print(final_paths_df)

# Convert the 'LinkID' and 'Mapped LinkID' columns of
    Links_Mapping_df into a dictionary
link_hash_to_id = Links_Mapping_df.set_index('LinkID')['Mapped LinkID
    '].to_dict()

# Map the 'Pickup Link' and 'Dropoff Link' in the final_paths_df
    using the dictionary
final_paths_df['Pickup Link'] = final_paths_df['Pickup Link'].map(
    link_hash_to_id)
final_paths_df['Dropoff Link'] = final_paths_df['Dropoff Link'].map(
    link_hash_to_id)

# Display the updated DataFrame
print(final_paths_df)
```

```
# Convert the 'Node' and 'NodeID' columns of nodes_mapping_df into a
    dictionary
node_str_to_id = nodes_mapping_df.set_index('Node')['NodeID'].to_dict
    ()

# List of columns to convert in final_paths_df
node_columns = ['Driver Origin', 'Rider Origin', 'Rider Destination',
     'Driver Destination'] + \
               [col for col in final_paths_df.columns if col.
                   startswith('Node')]

# Map each node column in final_paths_df using the dictionary
for column in node_columns:
    final_paths_df[column] = final_paths_df[column].map(
        node_str_to_id)

# List of all specific columns you mentioned plus dynamically
    identified 'Node' columns to convert to integers
columns_to_convert = ['Pickup Link', 'Dropoff Link', 'Driver Origin',
     'Rider Origin'] + \
                     [col for col in final_paths_df.columns if col.
                         startswith('Node')]

# Replace NaN values with 0 and convert each of these columns to
    integer
for column in columns_to_convert:
    final_paths_df[column] = final_paths_df[column].fillna(0).astype(
        int)

# Display the updated DataFrame
print(final_paths_df)

# Export the updated DataFrame to a CSV file
final_paths_df.to_csv('Final_Paths_Mapping.csv', index=False)

# Create a new DataFrame 'links_travel_times_converted' from '
    links_travel_times'
links_travel_times_converted = links_travel_times_no_tuples.copy()

# Convert the 'LinkID' and 'Mapped LinkID' columns of
    Links_Mapping_df into a dictionary
link_hash_to_id = Links_Mapping_df.set_index('LinkID')['Mapped LinkID
    '].to_dict()
```

```
# Map the 'LinkID' in the links_travel_times_converted using the
    dictionary
links_travel_times_converted['LinkID'] = links_travel_times_converted
    ['LinkID'].map(link_hash_to_id)

# Display the updated DataFrame
print(links_travel_times_converted)

# Convert the 'Node' and 'NodeID' columns of nodes_mapping_df into a
    dictionary
node_str_to_id = nodes_mapping_df.set_index('Node')['NodeID'].to_dict
    ()

# List of columns to convert in final_paths_df
node_columns = ['Origin', 'Destination']

# Map each node column in final_paths_df using the dictionary
for column in node_columns:
    links_travel_times_converted[column] =
        links_travel_times_converted[column].map(node_str_to_id)

# Display the updated DataFrame
print(links_travel_times_converted)

# Export the updated DataFrame to a CSV file
links_travel_times_converted.to_csv('links_travel_times_converted.csv
    ', index=False)
```

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