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João Carlos Quintal Lopes

DESIGNING A FLEET OF SHARED AUTONOMOUS ELECTRIC VEHICLES AND ITS CHARGING STATIONS THROUGH SIMULATION

Dissertação de Mestrado Integrado em Engenharia Civil, na área de Especialização em Urbanismo, Transportes e Vias de Comunicação, orientada pelo Professor Doutor António José Pais Antunes e pelo Doutor Gonçalo Gonçalves Duarte Santos e apresentada ao Departamento de Engenharia Civil da Faculdade de Ciências e Tecnologia da Universidade de Coimbra.

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Faculdade de Ciências e Tecnologia da Universidade de Coimbra
Departamento de Engenharia Civil

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Designing a fleet of Shared Autonomous Electric Vehicles and its charging stations through simulation

Dimensionamento da frota e dos pontos de carregamento de um sistema de veículos elétricos autónomos e partilhados através de simulação

Dissertação de Mestrado Integrado em Engenharia Civil, na área de Especialização em Urbanismo, Transportes e Vias de Comunicação, orientada pelo Professor Doutor António José Pais Antunes e pelo Doutor Gonçalo Gonçalves Duarte Santos

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ABSTRACT

Autonomous vehicles are the future of car mobility and the technology is already up and running presently. The era of self-driving cars is upon us and the transition from human drivers to robot drivers will happen sooner rather than later, and it is, therefore, important to prepare for it. This preparation comes in many forms and is done in many different areas. This work did not focus on vehicle technology nor on legislation and ethical questions, but rather on studying the mobility of a fleet of shared autonomous electric vehicles in a region and its respective road network. In particular, designing and simulating a hypothetical future transport service for the Region of Coimbra (NUTS III), in Portugal. The characteristics of this transport system are threefold: automation, ridesharing and electric power. An agent-based simulation model was developed to carry out this mobility study. Different maximum waiting times were tested, to verify how the vehicle fleet size varied. In addition, vehicle charging was studied in terms of quantity and location distribution. The obtained results show a logarithmic decrease in the vehicle fleet size, as maximum waiting time is increased.

Keywords: Autonomous Vehicles, Ridesharing, Electric Vehicles, Shared Autonomous Electric Vehicles, Simulation, Agent-Based Model

RESUMO

Os veículos autónomos são o futuro da mobilidade automóvel, com a tecnologia de mobilidade autónoma sendo já uma realidade. A era dos carros autónomos está a chegar e a transição de condutores humanos para condutores robôs irá se iniciar em breve, sendo, por isso, importante a preparação para essa transição. Esta preparação é feita de várias formas e em diversas áreas. Neste trabalho, o foco não foi na tecnologia automóvel, nem em legislação e questões éticas, mas sim, no estudo da mobilidade de uma frota de veículos autónomos elétricos partilhados (conhecidos popularmente em inglês como shared autonomous electric vehicles ou SAEV), numa região específica e na sua respectiva rede rodoviária. Mais especificamente, em conceber e simular um hipotético e futuro sistema de transporte para a Região de Coimbra (NUTS III), em Portugal. Há três características base para este sistema de transporte: automação, boleia partilhada (conhecido popularmente em inglês como ridesharing) e energia elétrica. Foi desenvolvido um modelo de simulação baseado em agentes (agent-based model simulation em inglês) para realizar este estudo de mobilidade. Foram testados diferentes tempos máximos de espera para verificar como variava o tamanho da frota de veículos. Adicionalmente, o carregamento dos veículos foi estudado em termos de quantidade e localização. Os resultados obtidos apresentam uma redução de curva logarítmica no tamanho da frota de veículos, à medida que o tempo máximo de espera aumenta.

Palavras-chave: Veículos Autónomos, Boleia Partilhada, Veículos Elétricos, Veículos Autónomos Elétricos Partilhados, Simulação, Modelo Baseado em Agentes

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LIST OF ABBREVIATIONS

AAODD: Autonomous vehicle Agent-based Overview, Design concepts and Details

ABM: Agent-Based Model

ADAS: Advanced Driver-Assistance Systems

AV: Autonomous Vehicle

CVT: Connected Vehicle Technology

D2D: Driving2Driverless

DDS: Door-to-Door Service

ETA: Estimated Time of Arrival

EV: Electric Vehicles

FCFS: First-Come, First-Served

LIDAR: Light Detection and Ranging

NUTS: Nomenclature des Unités Territoriales Statistiques (French for Nomenclature of Territorial Units for Statistics)

OD: Origin/Destination

ODD: Overview, Design concepts, and Details

P2P: Peer-to-Peer

PTS: Parallel Transit Service

R&D: Research and Development

SAE: Society of Automotive Engineers

SAEV: Shared Autonomous Electric Vehicle

SAV: Shared Autonomous Vehicle

SSS: Station-to-Station Service

TVTS: Tailored Time-Varying Transit Service

UDES: Urban Dynamics Education Simulator

UML: Unified Modeling Language

V2I: Vehicle-to-Infrastructure

V2V: Vehicle-to-Vehicle

VKT: Vehicle Kilometers Traveled

VMT: Vehicle Miles Traveled

1 INTRODUCTION

Although the concept of self-driving cars has been present for almost a century now, for most of that time it was more fiction than reality. But in recent years, the development and study of autonomous vehicles have increased substantially, turning theory into practice. And even though these systems are far from being fully accepted within society, the era of autonomous driving is coming, and we should prepare for it.

This preparation comes in many forms and needs to be done in many different areas. In this work we did not focus on vehicle technology per se, nor on legislation and ethical questions. The main focus of this work was simulating the environment and mobility of a fleet of shared autonomous vehicles in a region and its respective road network. More specifically, designing and simulating a hypothetical future transport service for the Region of Coimbra (NUTS III), in Portugal. The characteristics of this transport system are threefold: automation, ridesharing and electric power. Below, we will expose these characteristics individually. It should be noted that the developed work presented on this thesis is a small part of a wider project: “Driving2Driverless” (D2D).

The vehicles are autonomous, particularly with automation level 5. So, by definition, and using the Society of Automotive Engineers (SAE) International taxonomy (which defines 6 levels of automation: 0 to 5), the vehicles are fully automated, requiring no human attention whatsoever. Ridesharing is a key component of the system. This means that vehicles providing connections from one point to another may pick up other passengers along the route, possibly making detours, and therefore having multiple non-related passengers in the vehicle. The last component of the vehicles of the fleet is electricity. In other words, the vehicles are 100% electric powered. This also means several charging posts are needed. These three concepts join as one, in the form of an SAEV (Shared Autonomous Electric Vehicle). The fleet consists of many SAEVs travelling and providing transport services within the Region of Coimbra (SAE, 2018; Synopsys Automotive, n.d.-a).

Notwithstanding, the main goal proposed for this work, was to answer the following questions. How many vehicles should comprise the fleet? How many charging stations are necessary, and where should they be located? To try to answer these questions, we laid out and followed certain guidelines. A methodology was elaborated to design an SAEV transport system. The methodology involves the simulation of an agent-based model with interacting agents, based on input data and defined parameters.

This thesis is divided in 6 main chapters. The first chapter, Introduction, presents the main subject and explains the overall process of this work. In addition, it introduces, with further detail, some important concepts regarding this work. The second chapter, Literature Review, includes a global introduction into the subject of autonomous vehicles and mentions some of the potential benefits and major issues. Also, an overview of the existing literature regarding agent-based models and a study example are presented. The third chapter, Methodology, presents the general procedure, model development and analysis method. The fourth chapter, Case Study, introduces the case study, describes the data processing and presents some general statistics. The fifth chapter, Results, describes the results obtained from the simulations, interprets them and their significance. Finally, the sixth chapter, Conclusion, summarizes what was done in this work and suggests future work. Next, we will introduce some notable topics regarding the subject of this work: autonomous vehicles (including some terminology nuances), ridesharing, electric vehicles, shared autonomous vehicles, simulation and agent-based models.

Autonomous Vehicles

An autonomous vehicle is any type of vehicle that has the capability of driving itself from point A to point B, transporting cargo or people with it. It can refer to anything from a small AV working in a warehouse organizing goods, to a gigantic truck working in the mines. Although the word "vehicle" can refer to any kind of machine that transports people or goods (bicycles, cars, buses, trucks, boats, trains, airplanes, etc.), the term "autonomous vehicle" is usually applied to cars, also known as automobiles (a wheeled motor vehicle used for transportation) that can drive autonomously. An autonomous vehicle (AV) can also be referred as a self-driving car, driverless car, robotic car, and an automated vehicle (Intel, 2017; National Highway Traffic Safety Administration & HHTSA, 2018). Fundamentally, and citing the American electronic design automation company, Synopsys (Synopsys Automotive, n.d.-b): "An autonomous car is a vehicle capable of sensing its environment and operating without human involvement. A human passenger is not required to take control of the vehicle at any time, nor is a human passenger required to be present in the vehicle at all. An autonomous car can go anywhere a traditional car goes and do everything that an experienced human driver does.".

As previously mentioned, the Society of Automotive Engineers (SAE) defines 6 levels of driving automation, extending from level 0 (fully manual) to level 5 (fully autonomous). We can see these levels specified in Figure 1.1 (SAE, 2018; Synopsys Automotive, n.d.-a).

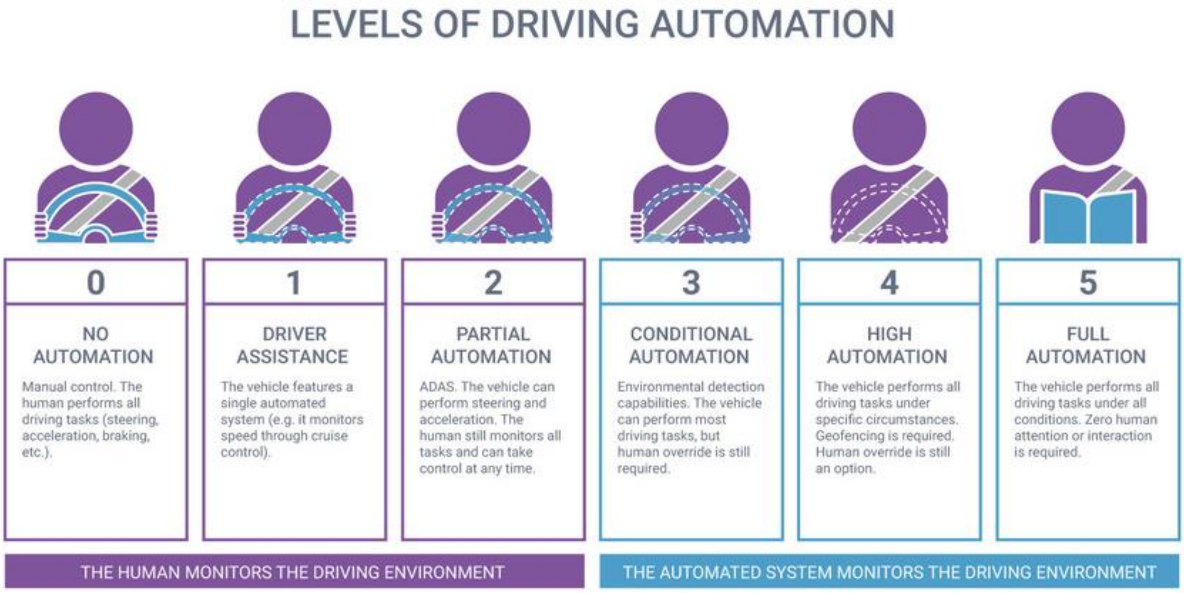

Figure 1.1: Levels of driving automation defined by the Society of Automotive Engineers (Source: (Synopsys Automotive, n.d.-a)*)*

Once again, citing from Synopsys' website, we can get a good overall and basic idea of how an autonomous vehicle works: "Autonomous cars rely on sensors, actuators, complex algorithms, machine learning systems, and powerful processors to execute software. Autonomous cars create and maintain a map of their surroundings based on a variety of sensors situated in different parts of the vehicle. Radar sensors monitor the position of nearby vehicles. Video cameras detect traffic lights, read road signs, track other vehicles, and look for pedestrians. Lidar (light detection and ranging) sensors bounce pulses of light off the car's surroundings to measure distances, detect road edges, and identify lane markings. Ultrasonic sensors in the wheels detect curbs and other vehicles when parking. Sophisticated software then processes all this sensory input, plots a path, and sends instructions to the car's actuators, which control acceleration, braking, and steering. Hard-coded rules, obstacle avoidance algorithms, predictive modeling, and object recognition help the software follow traffic rules and navigate obstacles." (Synopsys Automotive, n.d.-b). In later chapters, we will talk about some of the major benefits and challenges regarding autonomous vehicles.

There are some discussions in terms of terminology, such as the difference between "autonomous", "automated", "self-driving" and "driverless". Although these terms are used interchangeably by most people, there are some differences. The Society of Automotive Engineers uses the term "automated", opposing to "autonomous", since the term "autonomy" has a broader meaning, beyond the electromechanical. "Autonomy" comes from the Greek "autonomia", meaning "independence", with "auto" meaning "self" and "nomos" meaning "law", so something "autonomous" is something independent and that lives by its own laws. So, a fully autonomous vehicle would be self-aware and able to make decisions on its own. Thus, for example, you could command the vehicle to go to your home, but the vehicle may decide to go to the supermarket. On the other hand, a fully automated vehicle would obey your command and drive itself to the specified location (Autotrader, 2018; Levinson, 2017; Merriam-Webster, n.d.; Online Etymology Dictionary, n.d.; Synopsys Automotive, n.d.-b).

The term "self-driving" is usually referred to embody the whole idea of a car partially or fully driving itself from one place to another, so, it is a more general and broad term. Nonetheless, some people use this term to specify a vehicle that can drive itself, but that needs a human passenger always ready to override and take control. This falls into a level 3 (conditional automation) or level 4 (high automation) category, which means geofencing is required. In contrast, a level 5 vehicle, has full automation, can go anywhere and does not need human interaction. This is the type of vehicle that the term "driverless" usually refers to. These "driverless" or level 5 vehicles are expected to not have most type of controls, such as steering wheels and pedals (Autotrader, 2018; Levinson, 2017; Synopsys Automotive, n.d.-b).

In summary, these four terms are mostly used indistinguishably, but have indeed some formal differences. Notwithstanding, these differences are faint and already hazy, as their definition can vary depending on whom you ask, and even specialists in the field may give you different answers. David Levinson, transportation analyst and professor at the University of Minnesota, states the following (Levinson, 2017): "(…) I do not believe these differences can be preserved linguistically, even within the profession; the broad misuse and confusion will drown small differences of meaning.". This said, it should be noted that in this thesis, since the meaning and difference between the mentioned terms are already dubious, and in addition, the terms varied significantly within the research done, for practicality's sake, they are used interchangeably.

Ridesharing

Ridesharing or Ride-sharing, mostly known as carpooling and also referred as car-sharing (although car-sharing is nowadays used to designate a service with a fleet of vehicles available to its users), or lift-sharing, is the practice of sharing vehicle trips so that more than one person may travel in the same vehicle and avoids the need for others to drive themselves to a destination. In the article "Ridesharing in North America: Past, Present, and Future" (Chan & Shaheen, 2012), the authors split ridesharing into two types: "Ridesharing typically includes carpooling and vanpooling. Carpooling involves grouping travelers into a private automobile, while vanpooling entails individuals sharing a ride in a van. Ridesharing also includes more unique forms, such as casual carpooling.". The words ridesharing and ride-hailing are frequently used interchangeably nowadays, although some identify their differences. For a fee, a ride-hailing agreement is made between a car owner and a passenger who specifies a pickup location and destination using an app or website. A third-party manages this app or website and charges a fee for connecting passengers and drivers. Ridesharing, on the other hand, occurs when passengers are paired with others traveling in the same direction and share a ride (Cambridge Dictionary, n.d.; Commercial Driver HQ, 2018).

Ridesharing minimizes each person's travel expenses, such as fuel, toll fees, and the strain of driving, by having multiple people use one vehicle. Ridesharing is also a more ecologically beneficial and sustainable mode of transportation, since it mitigates pollutant emissions and road congestion, and reduces the parking requirements. Ridesharing is frequently promoted by authorities, particularly during periods of severe pollution or high fuel prices, since it optimizes occupancy rates (efficiency of mass passenger transport) by maximizing the vehicle’s seating usage (seats that would go unused if the car was just utilized by the driver), and thus increases the efficiency of the transportation system (Belz & Lee, 2012).

During World War II, ridesharing became popular in the USA, as a rationing strategy, and "car clubs" or "car-sharing clubs" were formed to facilitate ridesharing. To save resources for the war effort, the US Office of Civilian Defense requested local councils to encourage four employees to share a ride in one vehicle. It also developed the Car Sharing Club Exchange and Self-Dispatching System, a ride-sharing software. Due to the 1973 and 1979 oil crisis, carpooling resurfaced in the mid-1970s. Employee vanpools were established at Chrysler and 3M at the time (the first employer-sponsored vanpool program began April 1973, with the “3M Commute-A-Van”) (Chan & Shaheen, 2012; Oliphant & Amey, 2010).

Ridesharing is used mostly among people whose job is located nearby and who live in high residential density areas. It is also linked with transportation expenses, such as fuel prices and commute duration, as well as social indicators (time spent socially, eating or drinking; social and marital status). But people who stay more time at work, homeowners and elderly people are far less likely to rideshare (DeLoach & Tiemann, 2012; EU Shift2Rail, 2020; Tiemann & DeLoach, 2010; Viechnicki, Khuperkar, et al., 2015). Nowadays, 77% of American’s drive to work alone and less than 1 in 10 commuters rideshare to work (Viechnicki, Fishman, et al., 2015). In Europe, these values will vary a lot depending on country, region and ridesharing services available.

Different ridesharing solutions have been proposed to incorporate in a multimodal transportation system. It is recommended that the public sector collaborates with private mobility providers, in order to serve different types of demand. By integrating public transportation with ride-sharing companies, users have an alternative to driving their own vehicle. We may witness a drop in the number of households acquiring automobiles if cities continue to implement multimodal transportation. Ridesharing can change the way we see mobility, making it more sustainable and creating a new culture of vehicle use. In addition, it can help the transition to a multimodal Mobility Network in the near future, relying for this on new technology, social innovation, and autonomous vehicles (Bresciani et al., 2018).

Electric Vehicles

An electric vehicle is an automobile fully or partially powered by electricity, that uses one or multiple electric motors to generate propulsion, through power obtained via a collector system (where the electricity comes from extravehicular sources), or through an included battery. These cars can store energy in their batteries after being linked to a charging station or outlet, which is subsequently utilized by the electric engine (or engines). The amount of time it takes to charge an electric car is determined by its storage capacity, the amount of power it can receive, and the amount of power available from the charging station. The car's autonomy is determined by the capacity of the batteries, the engine's power, and the driving style (E-Redes, n.d.; EPA, n.d.; PC Magazine, n.d.).

Electric cars are nothing new, they date back to the 1800s, and they actually predate the first gasoline powered car, by a significant amount of time. The first car that surpassed 100 km/h was the electric-powered car “La Jamais Contente” in 1899. It is hard to indicate the precise moment of the electric car’s invention, or even its origin country and inventor. So, its invention is usually described as a series of breakthroughs. These breakthroughs came from many countries such as Hungary, the Netherlands, France, England and the United States (Encyclopædia Britannica, n.d.-a; Matulka, 2014; Paléo-Energétique, 2019).

In the early 1900s, there was no clear choice for which type of vehicle was better: electric, steam or gasoline. According to the Encyclopædia Britannica, in the USA, 40% of American automobiles were powered by steam, 38 percent by electricity, and 22 percent by gasoline. The electric automobile presented appealing selling advantages when compared to the gasoline car's unreliability, loudness, and vibration, as well as the steamer's difficulties and water requirements. The most noteworthy were its fast self-start (steam cars could take up to 45 minutes in the cold), quiet operation (gasoline cars were particularly noisy), and low maintenance. In addition to that, other pros, such as being easy to drive (especially when compared to steam and gasoline vehicles) and not having any intoxicating pollutants, made the electric vehicle a very popular and ideal choice. They were perfect for small trips around town, and terrible road conditions outside of cities meant that few automobiles of any kind could travel much far. It became easier to recharge electric automobiles as more people obtained access to electricity in the 1910s. It was only in 1908, when Henry Ford started mass-producing the famous Ford Model T, that electric cars’ popularity decreased. The Model T was significantly cheaper than the average electric car (about 1/3 or 1/4 the price). This affordability, plus the emergence of many gas stations around the country (which was in part due to the discovery of Texas crude oil), meant that gasoline powered cars could be quickly refueled (opposed to electric cars that took a long time to recharge) and thus allowed people to travel further, faster and cheaper than with electric cars. By the 1920s, further development of gasoline-powered cars (for example, the introduction of the electric starter, removing the need for a hand crank) and other advancements, such as road infrastructure (which incentivized people to travel more outside the city) lead to a critical decline in the use of electric vehicles, and by 1935, they were commercially obsolete (Encyclopædia Britannica, n.d.-a; Matulka, 2014).

For over a century, internal combustion engines have been the primary propulsion technology for automobiles and trucks, but electric power has still been commonly used in other vehicle types, such as railroads and smaller vehicles of all sorts. And although electric cars were first invented in the 1800s and several different vehicles were constructed in the 1900s, the Electric Vehicle industry did not take off until the turn of the 21st century. This new beginning for electric vehicles actually started in the 1990s, with environmental concerns becoming more relevant, especially between scientists and engineers, who backed by government departments, institutions and some companies, started working on more efficient cars and improving electric vehicle technology. In the present century, environmental concerns and conscious started to reach the general public, and the electric car' popularity has been increasing since. Nowadays, the electric car is widely seen as the future of the automobile, and hundreds of electric vehicle types are projected to be available worldwide by 2025. Currently, Tesla is the top brand in this sector, but almost all car brands on the market already have at least one electric model, and many of them have already declared their intention to transition to electric vehicles. Multiple benefits are associated with the implementation and wide use of the electric car, including economic advantages, quieter and easier driving, no direct emissions, current financial incentives, charging convenience (since electric infrastructure is everywhere, you can charge your car whether you're at home, at work, at supermarket, etc.), amongst many others. Most arguments against electric cars criticize their range and their charging time. But the truth is, in the last two decades, batteries have gotten significantly better (particularly due to the introduction of lithium-ion batteries) and astonishingly cheaper. Energy density has increased both per unit volume and per unit mass, while battery prices have plummeted, with lithium-ion batteries' price dropping 97% since 1991 (Ritchie, 2021). Regarding charging time, there are already fast-charging stations that take a small amount of time to charge. The most powerful public charger in the U.S. can charge a 95 kilowatt-hour battery in 16 minutes (if the battery can accept that power) (Stone, 2021). Modern fast-charging stations can charge 80% of an electric vehicle battery in about 30 minutes (to prevent damage, after 80% charge, the charging speed slows down) (Stone, 2021). The Tesla supercharging station can add more than 300 km of range in 15 minutes (Stone, 2021). Nowadays, many commercial electric models already have more than 500 km of battery range, with some reaching almost 700 km, this is not far from current fossil fuel vehicles' range (Electric Vehicle Database, n.d.-c). With new technological developments and more efficient manufacturing, these prices will continue to drop, while better and more efficient batteries and chargers will keep appearing. Notwithstanding, the fact is, most of the population do not even need to worry about range or charging time on a daily basis. In 2017, in the U.S., the majority (59.4%) of one-way household vehicle trips were less than 10 km and a staggering 95% were less than 50 km (Energy Department, 2018; Federal Highway Administration, n.d.). This means that even the lowest range models in the market today would be enough to serve most of the population on a normal daily usage. People can use their car during the day and, when they get home, simply leave it charging during the night. In addition, electric vehicles' production cost is expected to equal the one of fossil fuel vehicles in the next few years. Electric vehicles are an intrinsic part of the future of the automobile (Crabtree et al., 2015; Encyclopædia Britannica, n.d.-a; König et al., 2021; Matulka, 2014; The American Society of Mechanical Engineers, 2021; Waymo, 2021; Ziegler & Trancik, 2021).

Shared Autonomous Vehicles

As the name implies, a Shared Autonomous Vehicle (SAV) is an autonomous vehicle, that is "shared". So, it is a vehicle that can drive itself, but that is also designed to be shared between different users. These types of vehicles can be used both as time-shared vehicles, and time & space-shared vehicles. In the first case, only one person (client) travels at once, but after dropping that person at the destination, the vehicle is free to pick-up another client and transport him to its destination, and so forth. In the second case, the vehicle operates with ridesharing, which means more than one person can travel in the vehicle at the same time. While taking one passenger from point A to point B, the vehicle may pick-up other passengers along the route, or possibly do a small detour from the original route to pick-up the new passenger. There are different approaches used to optimize the vehicle's trips, and they will depend on many factors such as the demand, the fleet size, the maximum waiting time, maximum detour time, etc. SAVs and SAEVs (Shared Autonomous Electric Vehicles), also known as robo-taxis, are considered a game changer in mobility. They have the potential to significantly alter mobility patterns and urban planning, with associated huge socio-economic impacts. From the urban mobility point of view, benefits include a decrease in traffic congestion, incentives in tourism, improve walkability and mobility for everyone, increase safety, reduce parking demand, eliminate the need for car ownership, and many more. They can also benefit suburban regions, whether as a first mile or last mile option, by linking transport stations or hubs to homes, offices and other places of interest. These benefits and other important points regarding SAVs will be discussed in future chapters (First Transit, n.d.; Kampshoff et al., 2019; Narayanan et al., 2020).

Simulation and Agent-Based Models

A simulation is an approximate replication, usually assisted by computers, of a real-world process operation or system, over a set of time. Simulation modeling is a method of resolving real-world issues in a safe and effective manner. It gives a useful technique of analysis that is simple to verify, explain, and comprehend. Simulation modeling delivers important solutions across sectors and disciplines by providing clear insights into complicated systems (Anylogic, n.d.; Encyclopædia Britannica, n.d.-b).

Agent-based modeling (ABM) is a powerful simulation modeling method, that in recent years, has been used in a variety of applications, including real-world business issues. In the Anylogic website, the following is stated: “Agent based modeling focuses on the individual active components of a system. This is in contrast to both the more abstract system dynamics approach, and the process-focused discrete event method. With agent-based modeling, active entities, known as agents, must be identified and their behavior defined. They may be people, households, vehicles, equipment, products, or companies, whatever is relevant to the system. Connections between them are established, environmental variables set, and simulations run. The global dynamics of the system then emerge from the interactions of the many individual behaviors.” (Anylogic, n.d.; Bonabeau, 2002).

The simulation software used in this work was AnyLogic. It is a multimethod simulation modeling tool developed by The AnyLogic Company (former XJ Technologies), that works on Windows, macOS and Linux. The software allows the user to develop models using three simulation methods: agent-based, discrete event, and system dynamics, and they can be used in any combination. Anylogic includes various visual modeling languages: process flowcharts, statecharts, action charts, and stock & flow diagrams. The simulation software is designed and developed for business applications, and is used in industries such as supply chains, manufacturing, transportation, warehouse operations, rail logistics, oil and gas, ports and terminals, and mining. The AnyLogic Company is a multinational team operating from the US and Europe with a global network of partners. Some noteworthy clients include McDonald’s, British Airways, Coca-Cola, Facebook, IBM, NASA, Deloitte, Google, Nike, DHL, Intel, AIRBUS, BMW, Ford, and many others. Kyle Johnson, from IBM Global Business Services, Advanced Analytics and Optimization, states that “We chose AnyLogic to tackle our large complex problem because of the multimethod models you can use, the mix of agent based, discrete event and system dynamics is a very useful combination. My favorite part of AnyLogic is all the dashboard features, the great charts and business intelligence you can get from the agents that are working in the model.” (Anylogic, n.d.; Evgrafov, 2016).

2 RELATED LITERATURE

2.1 Introduction

In this chapter, we will introduce the subject of Autonomous Vehicles (AVs) by making an overview of some of the main topics associated with it. We will address many of the potential benefits of autonomous vehicles and some major issues to consider. For this purpose, we will base and guide ourselves on the analysis of the 2015 article "Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations" (Fagnant & Kockelman, 2015). In addition to that, we will complement the content of this chapter with other sources and more up to date information.

2.1.1 Background

The automotive and tech industries have made great strides in introducing computerization to a role that has been solely a human task for over a century: driving. The first efforts to develop autonomous vehicles focused on assisted-driving technologies. ADAS (Advanced Driver-Assistance Systems), which are electronic systems in a vehicle that assist the driver, first arrived on top-tier vehicles, but ultimately started appearing as features for lower vehicle categories, being widely available nowadays. These systems include adaptive cruise control, parking-assist/self-parking systems, emergency braking, backup cameras, amongst others. But a few companies have gone further on the matter, by creating self-driving cars (AVs). As mentioned in previous chapters, autonomous vehicles are vehicles that can drive themselves on multiple road environments, with non or little human involvement (the degree of human involvement depends on the level of automation). AVs have the capability to drastically alter the transportation network and its environment, as these technologies become successful and widely accessible (Fagnant & Kockelman, 2015; Heineke et al., 2017).

By avoiding deadly accidents, granting crucial mobility to the aged and disabled, increasing road capacity, saving fuel (energy), and reducing pollution, autonomous vehicles have the ability to radically alter transportation systems. Parallel developments in ride-sharing could contribute to the transition from owned vehicles to on-demand services. Many impacts may result from this change. Infrastructure investment and upgrading, land use, parking requirements and travel preferences are some examples. In addition, the passenger environment may be transformed as well, from the seat layout to what activities are practiced by passengers during the trip. For example, passengers may be facing each other or in reclining seats, and activities as working on your laptop, watching shows and movies, reading, eating, etc., activities otherwise impracticable, may be done while remaining safe (Fagnant & Kockelman, 2015; Hirz & Rossbacher, 2019).

The market share for AVs has grown significantly in the past decade. As of 2020, the global market volume is estimated to be approximately 6,700 units, with North America dominating the autonomous vehicle industry with a market share of about 46.5%. This can be attributed to the fact that adjustments in traffic regulations have been made, aiming at the incorporation of autonomous vehicle operations on public roads. Nonetheless, the current AVs global market volume is shy to say the least, when compared to forecasted future volumes. The global AV market is projected to grow at a compound annual growth rate (CAGR) of 63.1% from 2021 to 2030, achieving an estimated volume of more than 4.2 million units by 2030. Some of the major companies responsible for the development and presently operating in the market include Audi AG; BMW AG; Daimler AG (Mercedes Benz); Ford Motor Company; General Motors; Google LLC; Honda Motor Corporation; Nissan Motor Company; Tesla, Inc.; and Toyota Motor Corporation (Grand View Research, 2020).

2.1.2 Potential Benefits

There are some big and important differences between human driving and AV driving. Self-driving cars can be designed and programmed to operate as we see fit, and thus, we can bypass many human weaknesses. AVs do not blink, do not get tired, do not text while driving, do not take unnecessary risks, do not drunk-drive and do not break traffic laws (as long as we design them that way). In addition, their reaction times are faster, and they can be adjusted to improve traffic flows, fuel saving and reduced emissions. Next, we will address these topics with further detail (Fagnant & Kockelman, 2015).

Safety

In terms of safety, the potential benefits are obvious since driver error (human driver error) is accounted to be responsible for over 90% of all crashes (Fagnant & Kockelman, 2015). Human factors such as distraction, negligence or driving with excess speed are usually associated with the crash, even when the main reason for the accident is ascribed to the vehicle. Each year, 1.35 million deaths and up to 50 million injuries occur globally due to road traffic, with road traffic injuries being the leading killer of children and young adults (5-29 years of age) and the 8th leading cause of death for people of all ages (World Health Organization, 2018). The death rates in low-income countries are 3 times higher (27.5 deaths per 100,000 inhabitants) than in high-income countries (8.3 deaths per 100,000 inhabitants) (World Health Organization, 2018). In 2016, road traffic accidents were responsible for the loss of 25,600 lives and left more than 1.4 million people injured in the member states of the European Union (European Commission, 2018; Kovačević et al., 2020). A report from 2017 estimates that crashes in the EU have an annual economic cost of €270 billion (this includes lost productivity, medical costs, human costs, administrative costs, congestion costs, property damage), equivalent to 1.8% of the GDP (this value is believed to be an underestimation due to underreporting, the true cost is expected to be at least 3% of the GDP) (Wijnen & et al., 2017). In 2010, in the United States alone, 32,999 people died, 3.9 million were injured, and 24 million vehicles were damaged in motor vehicle crashes (Blincoe et al., 2015). These crashes had an economic cost of an estimated US$242 billion (this includes lost productivity, medical costs, legal and court costs, emergency service costs, insurance administration costs, congestion costs, property damage, and workplace losses), the equivalent of 1.6% of the U.S. GDP for 2010 (Blincoe et al., 2015). With AV technology getting better and better, and approaching a 100% AV penetration rate traffic scenario, the loss of lives and capital will predictably go down to reach very low values (scientist Bryan Hayes suggests that vehicle fatality rates per person-mile traveled could possibly reach those of aviation and railways, about 1% of current values) (Hayes Bryan, 2011). This being said, with the introduction of AVs, the potential benefits are considerable, both societal and economic (Fagnant & Kockelman, 2015; National Highway Traffic Safety Administration, 2008; World Health Organization, 2018).

Congestion and Traffic

Beside AV technology being developed to be safer, efforts have been made so that self-driving cars can also reduce congestion and fuel (energy) consumption, contributing to an enhanced traffic flow and lower emission rates. Through sensors and software, AVs can predict the leading vehicles' actions, such as accelerating and braking. This prediction results in a smoother braking and velocity adjustment, which in turn contributes to less traffic disrupting, fuel (energy) savings and less brake and tyre wear. Moreover, AVs can use current lanes and intersections much more efficiently, resorting to platooning for example. The more self-driving cars at an intersection, the more efficient the intersection is, furthermore, a solid lane of AVs greatly improves how many cars will go through the intersection. While this idea is still speculative, some research suggests that sophisticated systems could essentially eliminate intersection delays while reducing fuel consumption. Several of the improvements in congestion, rely not just on automated driving capabilities but also on coordination and cooperation between vehicles, via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The basis for connected transportation systems is a strong wireless communication network. Connected Vehicle Technology (CVT) applications depend crucially on reliable and continuous vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) data connectivity. Notwithstanding, since an appreciable portion of congestion is accredited to traffic incidents, a considerable congestion reduction may be achieved through safety benefits exclusively. AVs have been studied in a variety of scenarios to see how they can minimize traffic congestion. Congestion benefits from adaptive cruise control interventions and traffic monitoring systems could smooth traffic flows, at different levels of AV implementation, by attempting to decrease accelerations and braking in freeway traffic. Enabling vehicles to decrease the distance between them while travelling together, id est, platooning, improves fuel saving and increases highway capacity, while decreasing congestion. If all the vehicles in the platoon are equipped with sensors, the increase in highway capacity is estimated to be about 43%, whilst if they use both sensors and vehicle-to-vehicle communication, the increase is about 273% (Dey et al., 2016; Dresner & Stone, 2008; Fagnant & Kockelman, 2015; Milakis et al., 2017; Tientrakool et al., 2011).

Travel-Behavior

Travel behavior can also be substantially affected by the integration of AVs, since safety and congestion-saving impacts can induce shifts in travel behavior. New demands for roadway capacity may arise from different groups, such as individuals that do not have a driving license, the elderly and the disabled, for example. Ridesharing may become common as AV usage rises and lower fares are created. Since self-driving cars do not need a driver to park them, they can drop a passenger at its destination and then drive to a less-expensive parking location. Driverless drop-offs and pickups can become the predominant manner of travelling, with in-vehicle systems communicating with parking infrastructure. This same system can allow for nearby real-time rentals on a per-mile or per-minute basis, inducing carsharing and ridesharing. In addition, many studies expect that the number of owned vehicles will go down. Maintaining mobility levels, shared automated vehicles could replace from around 67% up to more than 90% of conventional vehicles (Milakis et al., 2017). This would mean a complete shift in urban design, as we would need less parking spots (particularly on city-center areas) and following this train of thought, projects become more feasible because we do not have to pay for all the extra land needed for parking, we could build more densely, housing becomes more affordable, and this cascade of effects goes on. So, the majority of these ideas draw towards an increase in vehicle miles traveled (VMT) and automobile-oriented development, although with less vehicles and parking spaces. We should note that despite the use of AVs possibly increasing VMT, the associated smoother travel should lead to reductions in fuel consumption and consequently less emissions (emissions per mile could be decreased). AVs' smart parking will also allow to save time and fuel usually lost searching for parking. So, cruising for parking and the associated frustration, may well become a thing of the past (Boesch et al., 2016; Bullis, 2011a; Fagnant & Kockelman, 2015, 2014; Larco, 2021; Milakis et al., 2017).

Freight Transportation

Regardless of whether we are right now, if we look around us, there is a good chance that most of the goods we see got to their destination by truck. In 2018, road transport accounted for about 75% of the total inland freight transport in the EU (Eurostat, 2020). In 2017, in the US, about 65% of freight shipments were done by truck (Bureau of Transportation Statistics, 2021). Notwithstanding, the freight transportation sector can potentially change drastically in the coming years. The autonomous vehicle technology that creates self-driving cars, can similarly be applied to trucks, creating self-driving trucks. Just as this technology has the ability to revolutionize the transportation of people, it also has the ability to revolutionize the trucking industry, by increasing fuel savings (and reducing emissions) and most importantly, by reducing and eventually eliminating altogether the need for drivers. Freight companies could significantly reduce personnel, with the need for only warehouse workers for loading and unloading cargo, plus some office workers. A sector that employs millions worldwide, will probably face resistance to such change. In 2015, 3.2 million people were employed as professional truck drivers in Europe (although these numbers have been decreasing due to driver shortage in Europe: in 2008 there were 300,000 more) (ITF-OECD, 2017). As of 2017, more than 3.5 million people work as truck drivers in the U.S. (about 1% of the population) (Cheeseman & Hait, 2019). Added benefits can be achieved by recurring to platooning, including even higher fuel saving, with a reduction of about 10% to 15% (due to reduced air drag) or even more when considering adaptive braking, and lower travel times (due to shorter headways) (Fagnant & Kockelman, 2015). Platooning has been successfully tested multiple times in the last years and thanks to an EU-funded initiative known as ENSEMBLE, multi-brand (Volvo Group, DAF, Daimler, Iveco, MAN and Scania) truck platooning has started taking place in Europe. Returning to the subject of AV technology, some companies are already using AV trucks. Waymo is a subsidiary of Alphabet Inc (Google's parent company) focused on the development of autonomous driving technology. Since 2017, when Waymo's trucking and local delivery program known as Waymo Via was launched, there autonomous Class 8 trucks have been tested in a wide variety of cities and environments in California, Georgia, Arizona, New Mexico and Texas (Waymo Via, 2020). The metals and mining corporation Rio Tinto currently runs more than 130 autonomous trucks, and in 2018, each truck was estimated to have operated 700 hours more (on average) than a conventional truck, with a 15% lower cost, and in addition, the automated system makes the mining operations safer (Rio Tinto, n.d.). Recently, Volvo Trucks has made an agreement with Brønnøy Kalk AS in Norway to provide its first commercial autonomous solution transporting limestone from an open pit mine to a close port. Other companies involved in the development and testing of autonomous trucks, include Tesla, Daimler, TuSimple and Embark, amongst others (Ackerman, 2021; Bullis, 2011b; Daimler, n.d.; Embark, n.d.; Fagnant & Kockelman, 2015; IRU, 2019; Kunze et al., 2011; Tesla, n.d.; TuSimple, n.d.; Volvo Group, 2018, n.d.).

Economic Impact

AV technology could have a big economic impact and monetary benefits could be enormous. Some estimations have been made in this sense, depending on the AV market penetration rate and some values have been suggested on a variety of different arguments and basis. Fagnant and Kockelman made estimates for AVs' annual economic benefits in the U.S. for three different penetration rate scenarios (10%, 50%, 90%). Their estimations for a 90% penetration rate scenario, indicate economic benefits up to US$201 billion and can even go further up to US$447 billion, if comprehensive crash costs are accounted, these include indirect economic factors like the statistical value of life and willingness-to-pay to avoid pain and suffering. The economist Adam Ozimek suggests that even with conservative values, the economic benefits for a full autonomous vehicle environment, in the U.S. alone, should be about US$642 billion ($317 billion from fatal crashes, $226 billion from non-fatal crashes, and $99 billion in time savings). Andreas Tschiesner, senior partner at McKinsey in the Automotive and Advanced Industries sector, states that every EU citizen spends about 40 min a day in a vehicle (usually a car). He also says that "If half of the time could be spent working, for example, dealing with mails, an extra one billion euro added value would be created every day". Although precise values and levels of impact remain unsure, we can already perceive the potential that AVs have to offer, with many and significant possible benefits for the population (Adam Ozimek, 2014; Bosch, n.d.; Fagnant & Kockelman, 2015).

2.1.3 Major Issues

AVs offer a plethora of possibilities, advantages, and obstacles, as well as behavioral shifts that affect how people engage with transportation systems. The pace and extent of any change to an AV-based system are far from certain; they will be highly influenced by AV purchase prices, as well as governmental licensing and liability requirements. Furthermore, AVs pose some unique threats, especially in terms of security and privacy. Even assuming that AVs will have an easy and quick implementation, a future system that makes the most out of AV capabilities will require in-depth research and careful development. Next, we will discuss some of the major obstacles to AV deployment (Fagnant & Kockelman, 2015).

Vehicle Costs

Vehicle costs are an important factor for AV implementation, if not the most important one in terms of barriers. The installation of new sensors, communication and guidance technology, and software for each vehicle are all needed technology for the development of autonomous vehicles. One of the biggest contributors to overall AV vehicle prices has been the LIDAR (Light Detection and Ranging) systems. Although some self-driving car developers have developed their AV technology without relying on LIDAR, the majority of developers deem these systems to be key components. In the first half of the previous decade, these systems had prices around US$70,000, constituting a considerable part of the total budget, and raising AV vehicle prices to over US$100,000 (Davies, 2019; Fagnant & Kockelman, 2015). In light of this, many companies started developing their own systems (for example: Waymo) or acquired LIDAR developers (for example: Argo, Aurora and Cruise). In 2017, Waymo started manufacturing its own LIDAR sensors with the goal of substantially reducing their AV production costs, by dropping one order of magnitude in the unit cost, lowering the price from

US$75,000 to about US$7,500 (Hawkins, 2019). Waymo will also sell their LIDAR sensors, with the first being the “Laser Bear Honeycomb”, however, Waymo will only sell them to clients who will not compete with its autonomous taxi business. Some companies as Luminar Technologies and Velodyne Lidar developed LIDAR sensors with a price range of about US$500 to US$1000 (Davies, 2019; Forbes, 2021). Notwithstanding that AV production costs are still a major barrier, the scenario has changed in recent years with the much cheaper LIDAR systems emerging. But despite the lowering costs of AV production and the agreed upon fact that technology has a trend of getting cheaper and more affordable with time, there is some disagreeing between specialists on how much time it will take for AV prices to reach the price range of conventional vehicles and on when will it be economically feasible to achieve widespread implementation. A survey released by the consulting firm Deloitte (Deloitte Global, 2020) shows consumers worldwide are still unsure about spending extra on AV and EV (Electric Vehicles) technology, however, there are indications that over the last years, consumers have become more willing to pay more for these technologies (as we can see in Figure 2.1; note that in this figure, the percentages are for people unwilling to pay more). According to Hensley et al., electric vehicle prices have been falling at a rate of 6% to 8% per year, indicating that it could take, for example, 15 years at an annual cost decrease of 8% to go from a $10,000 AV mark-up to a $3,000 mark-up (Hensley et al., 2010). As AVs transition from personalized add-ons and top luxury models to mass-produced vehicles, these costs will predictably reduce further (Fagnant & Kockelman, 2015; Luminar, n.d.; Nunes & Hernandez, 2019; Velodyne Lidar, n.d.).

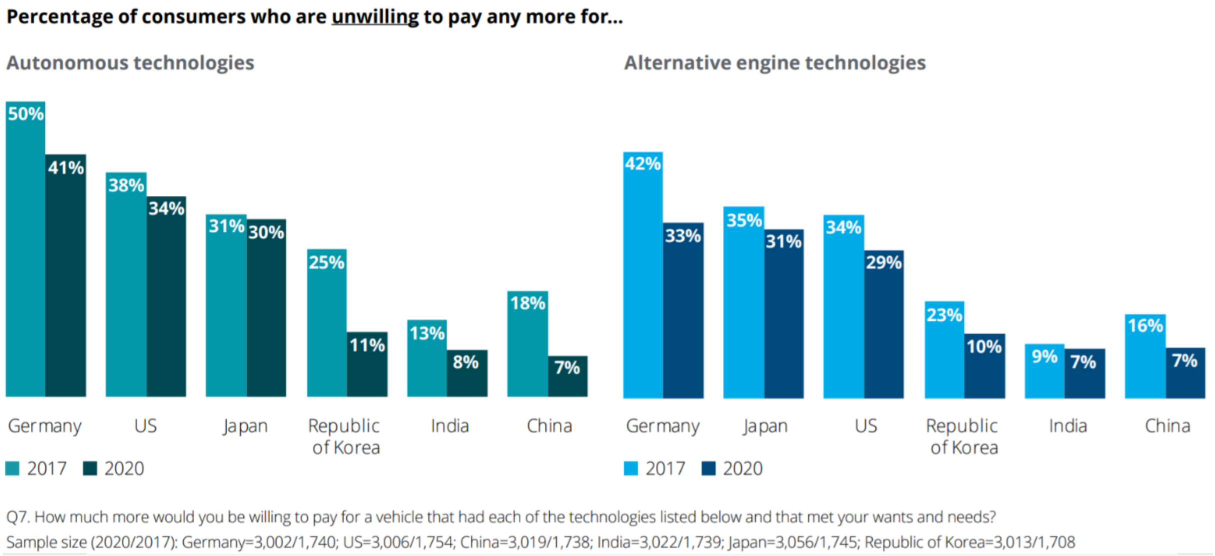

Figure 2.1: Percentage of consumers who are unwilling to pay more for AV and EV techonology (Source: (Deloitte Global, 2020)*)*

Legislation and Regulations

The automotive industry is collaborating with governments and research institutions to create and advance self-driving technology. Although self-driving developers are the ones responsible for creating and developing AV technology, lawmakers, local authorities and some institutions also have a crucial role in the implementation of AVs. At the moment, the United States is the country with most work done in this regard (mostly due to the presence of big tech companies and research institutions that started developing the technology early on). Notwithstanding, some countries such as China and Germany have been catching up (other countries whose governments or automotive and technology industries have been supportive and have produced new methods to assist the emergence of the autonomous vehicle industry include Australia, Canada, Hungary, Japan, Poland, South Korea and Turkey). Focusing on the first three mentioned countries and as stated in the "Global Guide to Autonomous Vehicles 2021", published by Dentons (one of the world's largest law firm) we have the following (Dentons, 2021):

- US – ["The United States does not have a federal regulatory framework currently in place to address autonomous vehicle testing and deployment. As a result, testing and deployment is regulated by a patchwork of state-centric laws. That patchwork is made up of 40 states and DC that have either passed autonomous vehicle legislation or are operating under executive orders. On Monday, January 11th (2021) the Department of Transportation released the Automated Vehicles Comprehensive Plan. (…) The document also lays out several steps the Department plans to take going forward. Additionally, The Department of Transportation and the National Highway Traffic Safety Administration issued an advanced notice of proposed rulemaking requesting comments on a new generation of safety standards for autonomous vehicles."];
- China – ["On February 10, 2020, 11 national ministries including the National Development and Reform Commission, the Ministry of Industry and Information Technology etc., collectively promulgated "the Innovative Development Strategy of Intelligent Vehicle." The strategy proposes that by 2025, the technology innovation, industrial ecology, infrastructure, regulations and standards, product supervision and network security system of China's standard intelligent vehicles will be formed. By 2035, China's standard intelligent vehicle system will be fully completed. To this end, the state will issue policies to promote the development of road traffic automated driving, and support the R&D and industrialization of common key technologies of intelligent vehicle infrastructure, as well as the construction of major projects of intelligent transportation and smart city infrastructure."];
- Germany – ["Overall, the German federal government welcomes further developments in the field of autonomous driving. Its aim is to strengthen the German economic

position in this sector. In its “Strategy for Automated and Connected Driving,” which was formulated in 2015, Germany has set the goal of ensuring that Germany remains the “lead supplier for automated and connected vehicles” and becomes the “lead market.” The introduction of autonomous vehicles into public road traffic is to be facilitated in particular, by adapting the legal situation. The effort to amend the legal structure began in earnest in November 2020 when Federal Minister Andreas Scheuer presented a draft bill to create a regulatory scheme for level 4 and level 5 autonomous driving.”];

We can see most of these government efforts are as recent as 2020 and 2021. These efforts have been increasing gradually, as new and better AV technology appears and, more and more people believe that the future of the automobile and transportation lies in automation. In the United States, the number of states that have introduced AV related legislation and/or issued executive orders related to autonomous vehicles has been increasing since the beginning of the past decade. China has enacted national regulations and road safety laws to encompass AVs (typically referred in China as “driverless vehicles”), with local regulations also being created. In Japan, the “Road Traffic Act” and “Road Transport Vehicle Act” were revised in 2019, with the operation of autonomous vehicles on public roads in mind. The legal issues regarding the operation of SAE level 3 autonomous vehicles have greatly decreased with these revisions, and there is developing work regarding the operation of SAE level 4 autonomous vehicles. Germany has benefited from being home to many major automotive companies (such as Audi, BMW, Mercedes, Porsche, Volkswagen, etc.), making it a leader in AV technology. In order to begin the regular operation of driverless vehicles, the German Federal Government adopted a draft law on autonomous driving in February 2021, with the goal of establishing an appropriate legal framework, by complementing current road traffic law regulations. In May 2021, the German Bundestag (German Federal Parliament) passed this draft law, intended “to amend the Road Traffic Act and the Compulsory Insurance Act – Act on Autonomous Driving” (19/27439). In Europe, besides the aforementioned Germany, multiple countries have permitted testing of automated vehicles on public roads, but most fall far behind the leading superpowers in many aspects. At an European Union level, some efforts have been made, especially with the “Regulation (EU) 2019/2144 of the European Parliament and of the Council of 27 November 2019”, which specifies requirements relating to automated vehicles and fully automated vehicles (this regulation shall apply from 6 July 2022, with exception to some articles that are already applied since 5 January 2020). (Dentons, 2021; e-gov (Japan), 1955; European Commission, 2019; Imai, 2019; National Conference of State Legistlature, 2018; National Police Agency (Japan), 2021; Nippon, 2021; Simmons & Simmons, n.d.).

The 1968 Vienna Convention on Road Traffic is an international treaty intended to increase road safety and to facilitate international road traffic by establishing principles to regulate traffic laws. One of the primary principles has been that a human driver is always in full control of the vehicle, and therefore is liable for its actions. For obvious reasons, this presented a legal problem for autonomous driving. But in 2016, an important regulatory milestone towards the deployment of AV technology was achieved, with the amendments to the 1968 Vienna Convention on Road Traffic. Automated driving technologies that delegate driving functions to the car will be explicitly permitted in traffic, provided that they are compliant with UN vehicle laws or may be bypassed or turned off by the driver. This will also involve eliminating UN Regulation No. 79's present restriction on automated steering functions (that limits driving speeds to below 10 km/h). (UNECE, 2016; United Nations, 1968).

Despite emerging legislation and recent regulatory progress, there is still an enormous amount of work to be done. AV technology is developing and evolving rapidly, and in many cases, the establishment of regulations relative to automated vehicles are not keeping up, many countries have fallen behind. And although treaties like the “Geneva Convention on Road Traffic” (United Nations, 1949) and the “Vienna Convention on Road Traffic” (United Nations, 1968), and the creation of legislation at international level, like regulation created by the European Commission have brought some internationally standardized regulation, ultimately, it is up to each country to apply its own regulations. Although regulations in Europe share the same fundamental basis, they remain somewhat fragmented. In the United States, the disparities are even seen at the national level, with each state having their own legislation. Without a coherent licensing framework and, standard norms and regulations, carmakers and software developers will have to examine their responsibility and how to proceed, country by country (or state by state). This can lead to redundant work and unnecessary overlap, demotivating manufacturers and delaying AV implementation (Dentons, 2021; Fagnant & Kockelman, 2015; Lexology, n.d.; National Conference of State Legistlature, 2018).

Liability and Ethics

An autonomous vehicle driving on public roads brings issues regarding responsibility and insurance involvement. Even though AVs will, as already mentioned, predictably make the roads a safer place, having a significantly lower percentage of error than humans, there will always be a percentage of error, as small as it will be, it will still exist. Even with an almost perfect AV, there may be situations where a crash is inevitable.

Regarding this subject, Fagnant and Kockelman give an example, with some interesting follow-up questions: [“For example, if a deer jumps in front of the car, does the AV hit the deer or run off the road? How do actions change if the deer is another car, a heavy-duty truck, a motorcyclist, bicyclist, or pedestrian? Does the roadside environment and/or pavement wetness factor into the decision? What if the lane departure means striking another vehicle? With a split second for decision-making, human drivers typically are not held at fault when responding to circumstances beyond their control, regardless of whether their decision was the best. In contrast, AVs have sensors, visual interpretation software, and algorithms that enable them to potentially make more informed decisions. Such decisions may be questioned in a court of law, even if the AV is technically not “at fault”. Other philosophical questions also arise, like to what degree should AVs prioritize minimizing injuries to their occupants, versus other crash-involved parties? And should owners be allowed to adjust such settings?”] (Fagnant & Kockelman, 2015). These liability issues are directly associated with the already covered “Legislation and Regulations” issues. Once again, we can understand the importance of having thorough and explicit legislation and regulations, regarding both manufacturing and legal matters, so that manufacturers will have guides for the process of creation and so that authorities can handle legal incidents without ambiguity (Fagnant & Kockelman, 2015).

Liability rules for product liability regarding self-driving cars remain far from internationally standardized, and legislators are lagging behind the quick moving world of AV. Product liability regulations in EU member states are based on the Product Liability Directive 85/374/EEC. For example, in Germany and France allegations may be filed against the manufacturer of a faulty product or the manufacturer of a component part. Regarding autonomous vehicles, the definition of the "manufacturer" (producer of product) is yet to be tested to see whether it includes the vehicle’s software designer. Each case will depend on whether the autonomous system is considered a component part of the vehicle or as a whole single product by the courts. If the system is deemed a component part (as brakes are, for example), the system's manufacturer will be responsible for any damages to the vehicle as well as any injuries or property damage sustained by the car colliding due to a fault in the system (European Commission, 1985; Lexology, n.d.).

The previously stated ethical questions are hard to answer and there is no universal morally right answer, but nonetheless, they have to be addressed. In 2018, the largest ever study on machine ethics was published in the popular scientific journal “Nature” (Awad et al., 2018). The Moral Machine, as is called the study, is an online platform developed in MIT (Massachusetts Institute of Technology), that creates moral dilemma problems and collects data about the decisions that people make between two outcomes (participants have to answer 13 laid out scenarios with a mix of variables: young or old, rich or poor, more or less people, etc.), where someone’s death is inevitable. The study found that the moral values that assist the participants deciding, vary by country, revealing cultural differences that authorities and AV developers should consider in order to facilitate self-driving cars’ public approval. The results show that the 130 countries involved in the survey can be divided into three groups: the first contains North America and many European countries where Christianity has been historically predominant; the second is constituted by countries such as Japan, Indonesia and Pakistan, where Confucian or Islamic traditions are more prevalent; the third and last group includes

Central and South America, and France and its past colonies. Beside the three groups more or less agreeing (independent of age, gender, or place of residence) on saving humans over pets and groups of people over individuals, significant differences can be found in the moral compass (see Figure 2.2). For example, the third group indicates a higher preference for saving females than the first and second group did. Studies like the Moral Machine can help in the debate about what decisions should the autonomous vehicles make in the case of an unavoidable accident. In the future, our cars will have to decide what do in critical scenarios, with our lives in the balance, and possibly, even decide to sacrifice us, as occupants, for the "greater good" (Awad et al., 2018; Maxmen, 2018).

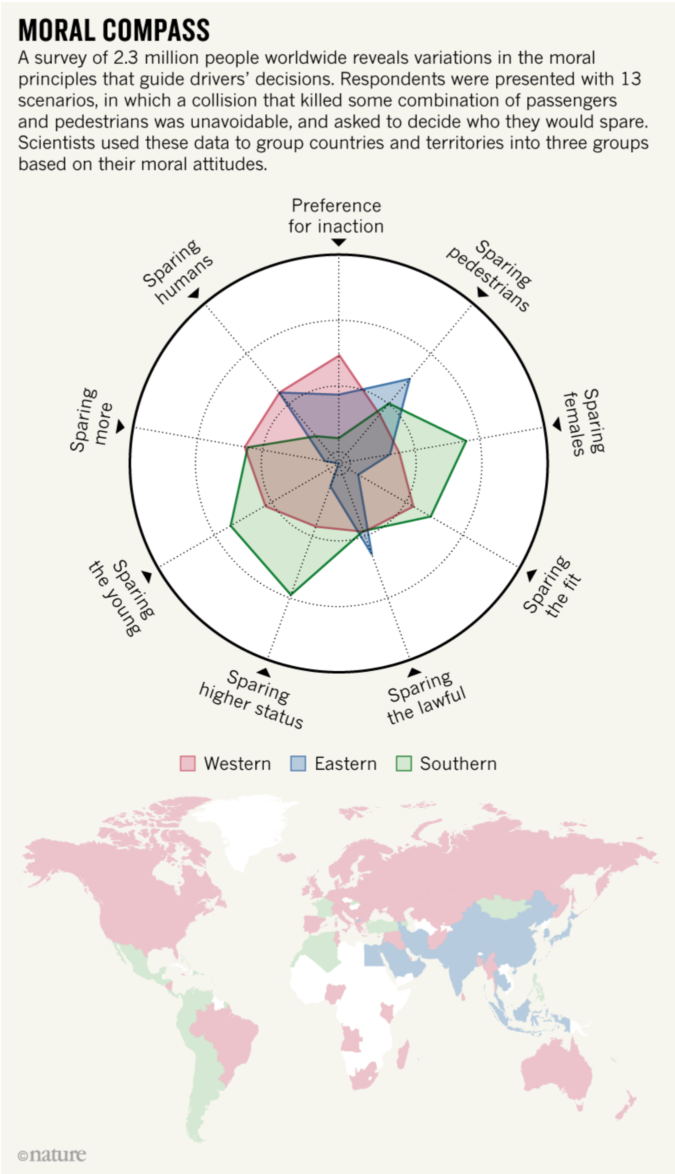

Figure 2.2: Moral Compass, The Moral Machine (Source: (Awad et al., 2018)*)*

Security

Electronic security is a major concern for transportation authorities, automotive producers, and future autonomous vehicle drivers. AVs and intelligent transportation networks in general can be targeted by computer hackers, dissatisfied employees, terrorist groups and hostile countries, resulting in crashes and traffic disruptions. Cars are getting progressively more sophisticated and connected, nowadays, even the average new vehicle depends on software that uses over 100 million lines of code. This is leading to vehicles that are more and more exposed, due to not just the quantity of code, but also, to its quality. The rate of technology progress is getting faster and faster, and companies, with fear of falling behind, may sometimes compromise rigor, in order to keep up with schedules and stay in the competition. As new features come out, this lack of carefulness could raise the probability of system errors and security vulnerabilities (Deloitte, 2017; Fagnant & Kockelman, 2015; GELLES et al., 2015).

To comprehend the scale of this threat, it is necessary to consider the issue in terms of effort-and-impact, as well as applying mitigation approaches used in crucial infrastructure structures of national significance. Currently, cyber-attacks are more often acts of spying (gaining unauthorized access to a device with the goal of collecting information) than sabotage (actively disrupting a system's regular operation) (Fagnant & Kockelman, 2015; Johnson, 2021).

For example, disrupting a vehicle's contact or sensors would involve a more complicated and sophisticated attack than merely gathering data, and disturbing the vehicle's control commands would be even more difficult. Plotting an attack to simultaneously compromise an entire fleet of vehicles, whether from a point source or from a system-wide broadcast over infected networks, would certainly present even more challenges to potential intruders. Large-scale attacks on AVs and associated networks should be especially difficult due to multiple security mechanisms, such as the seclusion of mission-critical and communication systems. Though experts agree that there is no such thing as a perfect defense, such procedures make attacks far more difficult to carry out while also reducing the amount of damage that can be done. In any case, the danger exists, and a security breach may have long-term consequences (Fagnant & Kockelman, 2015).

Privacy

Many advantages can come from vehicle communication systems, by benefiting from data obtained from other vehicles in the surrounding area, particularly information concerning traffic congestion and potential dangers. These systems use vehicles and fixed units as communication nodes in a useful data sharing P2P (peer-to-peer) network. As AVs and non-autonomous connected vehicles become more popular, and data sharing becomes more widespread, privacy issues are likely to increase. Some data-related questions emerge: “Who should own or control the vehicle's data? What types of data will be stored? With whom will these data sets be shared? In what ways will such data be made available? And, for what ends will they be used?" (Fagnant & Kockelman, 2015; Papadimitratos et al., 2009).

Crash data is expected to be held or made available by AV technology providers, and they would most likely be liable for damages if the AV is at fault in the case of an accident. However, privacy concerns may appear if a person is driving a car with autonomous capability at the time of the collision. People will predictably want to avoid their vehicle's data recorder to be exploited against them in court. But in truth, this is simply an extension of an ongoing concern, since in many places, most new vehicles sold already have in-vehicle data recorders. Currently in the United States, about 96 percent of new passenger cars have identical incident data recorders that describe vehicle behavior in the seconds leading up to and after a collision, although less complete (Consumer Reports, 2014; Fagnant & Kockelman, 2015). In the European Union, these "black boxes" as they are popularly known, have been present in the market for many years, but their use is not as widespread as in the US. Notwithstanding, the use of these data recorders is usually considered beneficial, since accident investigators can use it to determine more precisely what happened and, to improve safety of future vehicles and accidents (European Commission, n.d.; Fagnant & Kockelman, 2015).

Some more controversial concerns may arise with the providing and possibly storing of AV travel data (routes, destinations, schedules, etc.) to government agencies systems. Without adequate protection, this information may be used by government employees to trace people, or sent on to law enforcement authorities for unrestricted monitoring. People may also be concerned about the potential commercial uses of vehicle travel info, such as personalized ads, for example (Fagnant & Kockelman, 2015).

Despite the well-placed concerns, AV data can have huge advantages, if disseminated and used responsibly. The information obtained can help transportation network administrators and developers with future planning and improvements, and assist with the transition from a gas tax to a VMT fee, as well as the implementation of congestion pricing systems based on place and time of day, and can be used to increase efficiency and trip quality for passengers. Such information could also be useful to law enforcement, and economic revenues from ads could bring down AV costs. We should also keep in mind that this kind of concerns, like personalized ads, are already a common thing in our everyday life. Through a method known as "retargeting", companies track consumers' shopping habits to then provide customized advertisement. Companies like Google build up an ad profile based on your searches, behaviors and estimated preferences, so that they can tailor ads for each person. And as a matter of fact, studies show that the majority of consumers actually prefer tailored ads, making this a minor issue in the subject of AV. Any decision to improve traveler privacy should be weighed against the advantages of sharing data (Bleier & Eisenbeiss, 2015; Fagnant & Kockelman, 2015; Google, n.d.; Pauzer, 2016).

Missing Research

Although AVs are now a reality and already operating on public roads (mostly in limited and well-defined areas, and driving along specific routes), there is still much uncertainty regarding the impacts of a partial or full AV deployment. As stated, AVs are already driving among us (in very specific cases) and the number of operating AVs will predictably continue on rising, but it is still unsure when will self-driving cars constitute a significant portion of the vehicle fleet of the AV research leading countries, let alone the rest of the modernized world. Existing literature has mostly investigated the technological aspects of autonomous vehicles and their implications on the driver and driving environment, however, there is few research with a more comprehensive view, regarding other direct and indirect potential impacts of AV adoption (Fagnant & Kockelman, 2015; Milakis et al., 2017).

2.2 Agent-Based Model

In this chapter, we will make a general overview of the existing research regarding agent-based simulation of automated vehicles. For this purpose, we will follow more or less, the 2020 article "Agent-Based Simulation of Autonomous Vehicles: A Systematic Literature Review", published in IEEE Access (Jing et al., 2020), complementing with other sources, including the very recent systematic review article from July 2021, "A systematic review of agent-based models for autonomous vehicles in urban mobility and logistics: Possibilities for integrated simulation models", that was published in the Computers, Environment and Urban Systems journal (Li et al., 2021), while the previously referred article was already analyzed and the writing of this chapter was already ongoing. In addition to that, we will also have a quick look to the 2019 research article, "Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model", published in the Journal of Advanced Transportation (Wang et al., 2019).

2.2.1 Background

Previously we talked about several potential benefits related to the use and widespread implementation of AVs, such as turning the roads into a much safer environment, decreasing congestion and traffic, lowering emissions and inducing fuel savings, decreasing fleet size and need for parking, increasing accessibility, freeing up time for drivers, and generating huge economic benefits, amongst others. Notwithstanding the huge positive impact that AVs may have, their impact is uncertain, since there is yet no extensive use of fully autonomous vehicles.

For this reason and due to the fact that real-life testing of AVs is expensive, the construction of simulation systems is essential for acquiring vast amounts of data at a low cost. Additionally, legal constraints and safety issues constitute other real-life testing barriers, which can be surpassed with simulation operations. Complex systems such as an AV network require that multiple variables and scenarios be tested in a variety of environments, and agent-based simulation is a suitable option for this purpose (Jing et al., 2020).

Agent-Based Models (ABMs), as described in a previous chapter, are computational simulation models that focus on the individual entities and their interactions with each other and the environment. Compared to other models and simulation methods, the ABM is improved in many aspects, like flexibility and hierarchy, and being more intuitive, as they represent objects as individual things. Furthermore, it factors in the diversity and the different characteristics for each agent (humans and vehicles). The model analyzes the system from a microscopic scale to a macroscopic scale perspective. AV transportation systems are complex, and therefore we must examine the interplay of the interrelated components in the system, this includes people, cars, the road grid, and the environment (Jing et al., 2020).

As computer processing power has increased, researchers have built several agent-based models with increasingly more features and with scenarios ever more similar to the real-world. Each investigator develops the models for their own purpose, concentrating on their defined main variables, with some models being more complex than others. This and the use of different simulation platforms results in a wide variety of solutions to approach in the real world. While some researchers may focus on the travel and environmental implications of AV, others will concentrate on the parking requirements associated with the implementation of AV. Other main concerns include the performance of AV systems, the traffic congestion caused by AV and the model share of AV (Jing et al., 2020).

In the last years, Agent-Based simulation of AV has seen a considerable growth in quality and quantity of research, with multiple papers being published on this topic, thus raising the need for a standard protocol for comparison. The following chapter’s analyzed information was obtained through the use of the ODD (Overview, Design concepts, and Details) protocol (the “ODD protocol” was published in 2006 with the purpose of describing and standardizing Individual-Based models and Agent-Based models) and some of the complementary information was obtained through the use of the more recent and specific variant AAODD (Autonomous vehicle Agent-based Overview, Design concepts and Details) protocol (Grimm et al., 2006; Jing et al., 2020).

2.2.2 Overview of existing literature

From the main systematic review in question, 44 valid papers were chosen from the selection process. This process included the retrieving of a total of 10,769 papers (including duplicates) from the following databases: Web of Science, ScienceDirect, SPRINGER LINK, IEEE Xplore and TRID; and their consequent selection by a number of criteria (check the original article for more detail on the process of selection). However, from the selection process of the 2021 systematic review, a total of 80 papers were selected (73 publications in mobility and 7 publications in logistics). While the papers from the 2020 systematic review were searched in May 2019, the more recent systematic review's authors carried out the research in December 2020, with only papers issued after 2015 being filtered. Although the number of chosen papers varies due to the selection process criteria, we can already verify a significant increase of papers on the subject in the period between the researches of these two reviews (less than 2 years), with the majority of the papers being published in 2019 and 2020 (Jing et al., 2020; Li et al., 2021).

Date and geographic distribution

In terms of date distribution of the papers/articles, as we can see from the plots in Figure 2.3 and Figure 2.4 (2020 review and 2021 review respectively), both systematic reviews reflect that the interest and work done on the subject has and is increasing significantly throughout the years, with most of it being done recently (note that in the 2020 review, although 2019 has less published work than previous years, the research for this systematic review was done in May 2019, not even halfway through the year). In addition to that, the increase over the years has been not only in quantity, but also in quality, as results obtained via AAODD show the average scores of publications obtained annually grow throughout the years, with AV systems in ABMs getting more complex by compounding diverse technical options and ABM methods getting more mature, leading to more realistic simulation scenarios (Jing et al., 2020; Li et al., 2021).

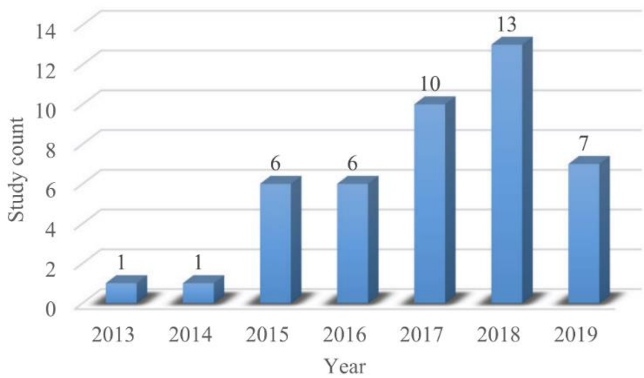

Figure 2.3: Number of papers per year, 2020 review (Source: (Jing et al., 2020)*)*

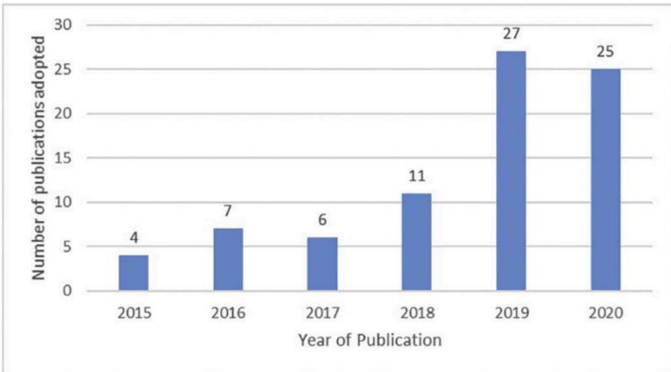

Figure 2.4: Number of papers per year, 2021 review (Source: (Li et al., 2021)*)*

The 2020 review's geographic distribution (seen in Figure 2.5) of case study areas used in the agent-based models research of AV follows the aforementioned trend that presently places the United States of America as the most developed country (in various aspects) on the subject, with Europe not far behind. Although China is nowadays one of the leading countries in AV technology (as already talked about in previous chapters), none of the 44 papers selected are from the country. The authors of the article point out that this may be due to the fact of research data not being publicly available and that all reviewed articles are in English. The 2021 review shows a somewhat similar trend, but with European countries as a whole, catching up with the USA, and Asian countries appearing with a more significant number of case studies than before (see Figure 2.6). Additionally, some studies adopted theoretical networks that are not based on real-world road networks (Jing et al., 2020; Li et al., 2021).

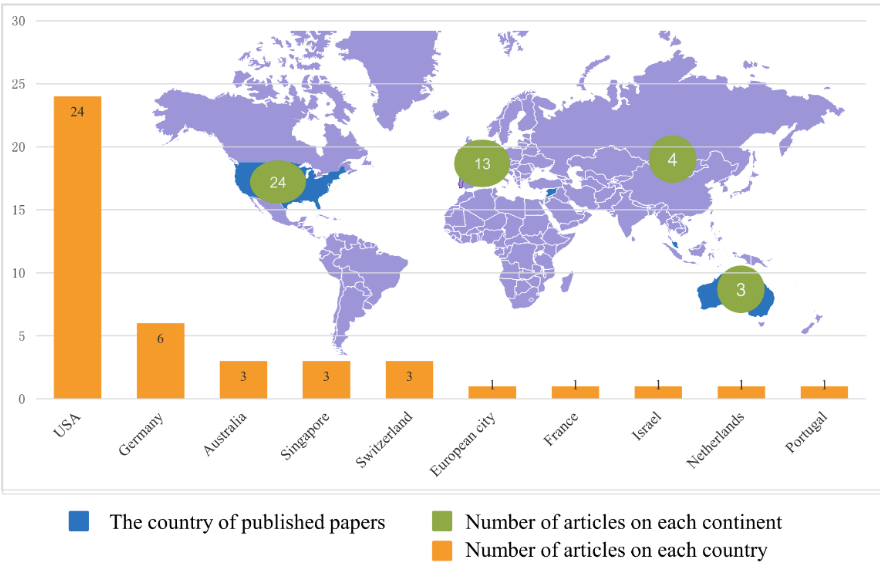

Figure 2.5: Geographic distribution of papers, 2020 review (Source: (Jing et al., 2020)*)*

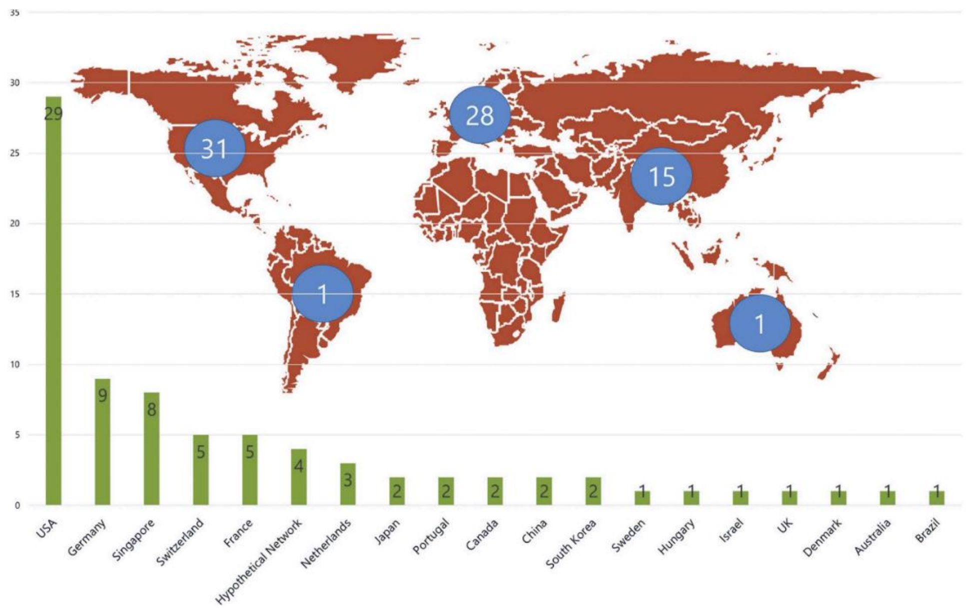

Figure 2.6: Geographic distribution of papers, 2021 review (Source: (Li et al., 2021)*)*

Simulation platforms

Due to the infancy of fully autonomous AV technology and the high costs of field testing, several simulation platforms are being used to investigate the implications of autonomous vehicles' adoption. The ABM community has created toolkits to assist researchers in creating customized ABMs. Figure 2.7 and Figure 2.8 show the platform distribution of the analyzed papers in the 2020 and 2021 systematic review, respectively. Many different platforms are used, such as: MATSim, SimMobility, AnyLogic, MATlab, amongst others. Toolkits are mostly based on existing platforms, but some researchers create ABMs without the use of platforms. The most popular choice is usually MATSim, which is programmed in Java and has an activity-based and agent-based open-source framework (Jing et al., 2020; Li et al., 2021).

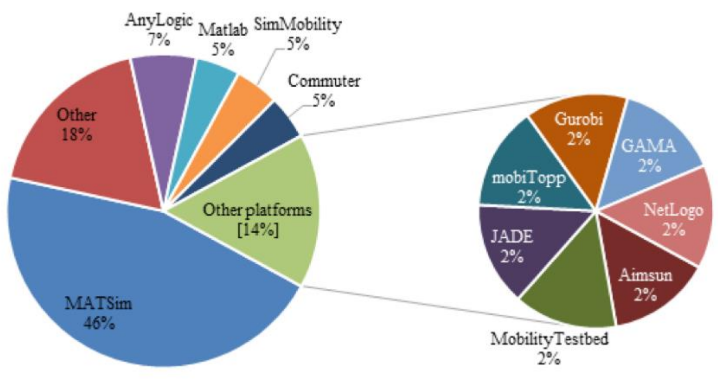

Figure 2.7: Platform distribution of papers, 2020 review (Source: (Jing et al., 2020)*)*

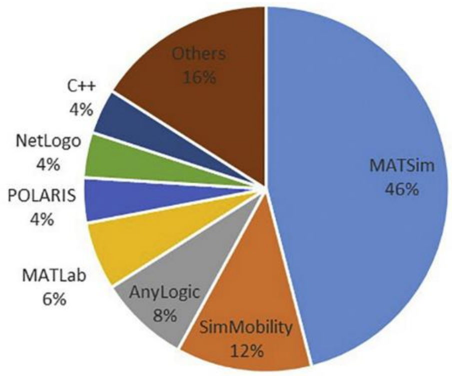

Figure 2.8: Platform distribution of papers, 2021 review (Source: (Li et al., 2021)*)*

Data collection

There are many sources through which one can obtain data. For the studies in question, most obtained data is regarding environments, populations, and validations.

The cornerstone of ABMs in transportation is a certain population of individuals with varied traits and behaviors, so it is important to collect reliable and representative data for each case. To generate a population, the most commonly used information is population census (regarding socio-demographic data), household travel surveys (regarding the agents' travel demand) and services plus travel data (regarding the locations of the agents' activities). Regional taxi datasets are an alternate source for creating travel demand since they are more available over longer periods of time than travel surveys and match better with SAV characteristics, although there are some downsides, such as the neglect of mobility regarding other transportation modes, resulting in a major percentage of overlooked trips. Other sources of data include cell phones, GPS devices, surveys, amongst others. Ideally, for a more complete depiction of the population, researchers will combine data from multiple sources (Hörl & Balac, 2021; Hyland & Mahmassani, 2020; Li et al., 2021; Liu et al., 2020).

In terms of the model environment, 95% of the models examined are based on real maps, ranging from minor regions like heavily populated urban areas and links between railway stations and universities to national level simulations. The majority of publications that use real-world situations utilize online open-source map datasets (example: OpenStreetMap), while some use grid-based cities. Typically, these models are limited to smaller service regions with a larger trip density. Another type of simplification are grid-based networks, allowing just horizontal and vertical mobility, although due to the advancement of computing power, this option becomes more uncommon after 2017 (Kim et al., 2019a, 2019b; Li et al., 2021; Scheltes & de Almeida Correia, 2017; Sheppard et al., 2019).

As autonomous vehicles are still in an early phase, currently, there is very little to none real-life data that can be used to validate projected future scenarios. Researchers may, however, evaluate whether the simulation is accurate by comparing traffic performance in a simulation without AV to the respective real-world data, which is primarily based on traffic count data. Nonetheless, it is uncommon for most studies to show their validation data (Li et al., 2021).

Key variables in the simulation and model assumptions

Reality is very complex and there are virtually infinite different scenarios. So, researchers developing ABMs, use many assumptions to simplify it. Depending on each case, various variables and assumptions can be used in the model.

In Figure 2.9, we can see the most common critical variables considered in simulations, that affect the performance of the system. Fleet size being the most common and followed by demand, strategy, ridesharing, vehicle range, travel modes, pricing scheme, configuration of stations, service area, refuel/recharge time, vehicle capacity, maximum waiting time and cruising time (Jing et al., 2020).

Fleet size unavoidably has an impact on the operation of the system and is related to vehicle replacement (market penetration) rate. Demand is a primary factor since it comprises two important factors: the trip demand and the AV penetration. Many different AV's market penetration rates are assumed by researchers, from full penetration (100%) to intermediate and low values of penetration, with this broad variation depending on each situation and purpose of study. The strategy variable can be distinguished in many types, such as scheduling strategies, assignment strategies, deployment strategies, operation strategies and hailing strategies, amongst others. Ridesharing is also an important variable to take into account, since it can reduce fleet size significantly. Additionally, some studies consider ridesharing optional, with individuals having a certain "willingness to share" (0-100%) and the vehicles can be ridesharing or not. Generally, the accepted deviation for ridesharing is less than 10km or 10% to 40% travel time increase. Vehicle range is usually an important factor when the simulation is regarding electric vehicles, with considered ranges varying from 100km to multiple times that number. Taking into consideration different travel modes will obviously impact the system's performance and some studies have tested and compared AV implementation with different transport modes present in mixed scenarios. Pricing schemes are usually used to explore AVs market potential. The configuration of stations is normally split into parking stations and charging stations, with the most important being charging stations since it can strongly impact fleet size and system performance. In most cases, the service area is a fixed variable for a well-defined region, however, some studies have examined how changing the service area can affect the system's performance. Refuel/recharge time is also an important factor, once again with particular interest when regarding electric vehicles, since electric charging times can be significantly higher than refueling if fast charging is not considered. Vehicle capacity is the vehicle's capability to carry individuals and usually varies between 1 and 4 passengers. Passenger waiting time, although not in particular relevance in Figure 2.9 (since it is commonly used as a simulation output indicator, as we will see later), is a major factor in transportation ABMs, and refers to the time between placing an order and the moment the AV arrives. A waiting time limit is typically established, in order to guarantee an acceptable service level. Waiting time will range from about 5 to 20 min usually, with some studies testing multiple limits to obtain minimum fleet size, and only a few studies assume that agents will wait indefinitely for the transport service. Some researchers go further, by giving individuals in the simulation the possibility of choice of transport mode and an associated contemplation period to assess transportation offers, although most models neglect this process. The impact of cruising time and other variables, such as certain electric vehicle assumptions, is also examined in a few models (Dandl et al., 2019; Hyland & Mahmassani, 2020; Jing et al., 2020; Li et al., 2021; Lokhandwala & Cai, 2018).

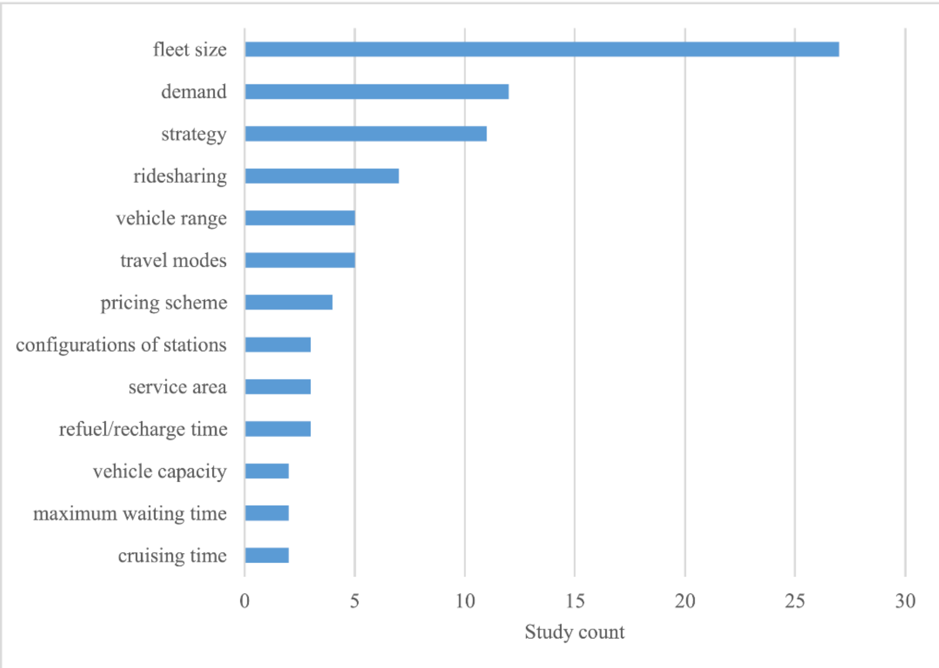

Figure 2.9: Critical variables considered in the simulations, 2020 review (Source: (Jing et al., 2020)*)*

Model execution and scenario variations

Before carrying out an ABM simulation, there are some processes and strategies to be considered. Additionally, ABMs and their characteristics can be adapted and readjusted fairly easily, thus creating scenario variations of which results can be compared and assessed.

With the network and mobility data sorted out, typically, the next thing to do is to generate sample vehicle trips through methods such as Monte Carlo and Poisson distribution. Depending on whether fleet size is or is not a variable, it may be necessary to determine a preliminary fleet size, with two major methods usually being identified: SAV "seed" simulation, where a central dispatcher generates vehicles until the demand is met within a specified reach of usually 20 minutes; and through changes in the average waiting time, where vehicles are added up until the moment when the waiting time ceases to decrease appreciably. (Chouaki & Puchinger, 2021; Fagnant & Kockelman, 2018; Li et al., 2021, 2020; Zhang et al., 2015).

The most popular operational strategies associated with SAV can usually be categorized into one of these types: Dispatching Strategy, Rebalancing Strategy and Parking Strategy (Figure 2.10).

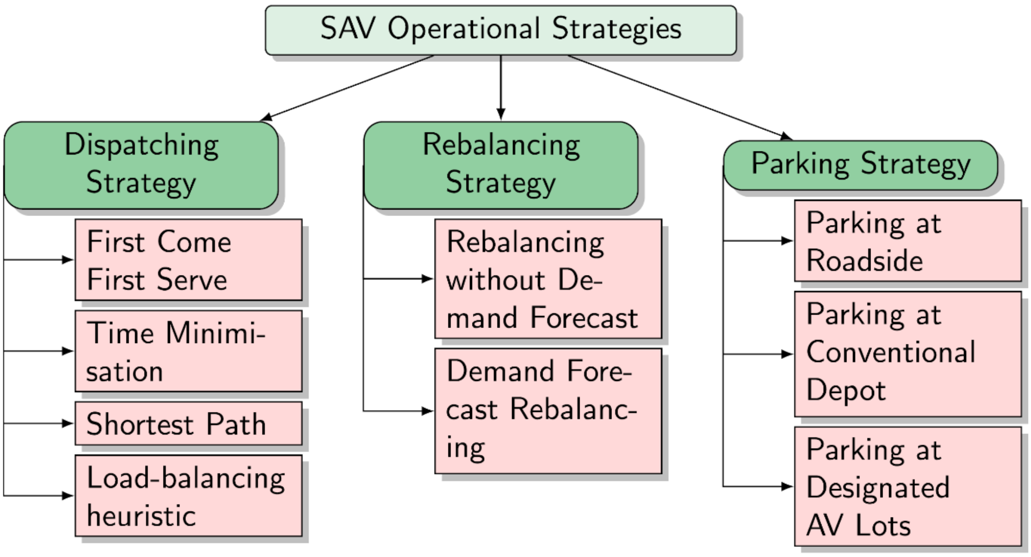

Figure 2.10: Reviewed SAV operational strategies, 2021 review (Source: (Li et al., 2021)*)*

Dispatching strategies can be simple or complex, and it is assumed that the clients' decision-making is instantaneous. In the "First Come First Serve" method, vehicles are sent to the clients as soon as an order is placed, while in the "Time Minimization" and "Shortest Path" methods, the vehicles are dispatched according to their distance from the client. But in order to obtain more efficient results, particularly when regarding peak hours, some researchers apply a mixed method known as "Load-balancing heuristic". In this method, dispatchers monitor if there is more vehicle supply than request demand, and according to that balance, they can alter between the "First Come First Serve" and "Shortest Path" methods. In the case of non-instantaneous decision-making, dispatchers can opt to send a vehicle to the client, even when the request is not confirmed, although the efficiency of this method is tied to the request confirmation rate (Li et al., 2021).

Rebalancing strategies, also known as vehicle relocation, might enhance SAV service levels, but it may also raise overall congestion owing to the increased number of empty vehicle kilometers traveled (VKT) during rebalancing/relocation, and as a result, in certain situations, rebalancing is limited to specified hours or demands. There are two vehicle relocation strategies essentially: one has predefined criteria (such as a certain distance limit, or a minimum time limit) and doesn't take into account demand forecasting; the other is adaptable by taking into account demand forecasting, through data such as vehicle location, current demand and availability (spatial-temporal demand forecast strategies and demand-supply balancing strategies are some examples) (Li et al., 2021).

Although parking strategies can reduce fleet size, lower passenger waiting times and improve equity in the provision of transportation services, prior to 2019, the majority of articles did not include AV parking strategies, and simply allowed AVs to park on the side of the road. This approach raises some concern, since it might interfere with the normal operation and will probably affect network performance. So, other options, such as warehouse parking, mall parking and dedicated AV parking, have been tested lately. When considering electric vehicles, these parking can be associated with charging posts, so they can recharge off-service while parked. Notwithstanding, empty VMT/VKT and some other cons are predictably going to arise with these parking strategies (Li et al., 2021).

As already mentioned, scenario variations are common, since most can be done quickly and without too much effort. Many researchers include more than one scenario on their ABMs, and these scenario variations can be classified into four viewpoints (Li et al., 2021):

- AV Demand, where the concern is with any factors that impact passengers' willingness to utilize autonomous vehicles and sharing rides, and variable scenarios are obtained by directly changing customer demand or by creating behavior control systems that indirectly affect the demand;
- AV Supply, which concentrates on the characteristics that influence how many vehicles are offered, with the most prominent by far being fleet size (in the beginning, increasing the fleet size is beneficial for achieving rapid gains in service quality, but beyond a certain point, the efficiency begins to decline, and it becomes more advisable to alter other factors, such as vehicle range, service area, passenger capacity, electrifying vehicles, etc.);
- Operational Strategy, where the focus is on the already discussed popular strategy variables such as dispatching, rebalancing and parking, but also on others such as

platooning, multiple different charging schemes (when regarding electric vehicles), geofencing, pre-booking, shifting service between door-to-door and terminal-to-terminal (time tailored), amongst others;

- Other Infrastructure, where other road components that are not directly associated with AV, but have an indirect impact on their operation, are addressed. Here we divided them into "Other modes of transportation", in which scenarios are regulated by either changing public transport availability or by altering other factors that indirectly affect their preference, and "Network", where different scenarios emerge essentially from changing the capacity and adding links in the network.

Figure 2.11 sums up the categorized factors, with the numbers between parentheses indicating how many articles used those factors (out of the 73 articles regarding mobility reviewed in the 2021 systematic review) and "Others" relates to variables that were only used once (Li et al., 2021).

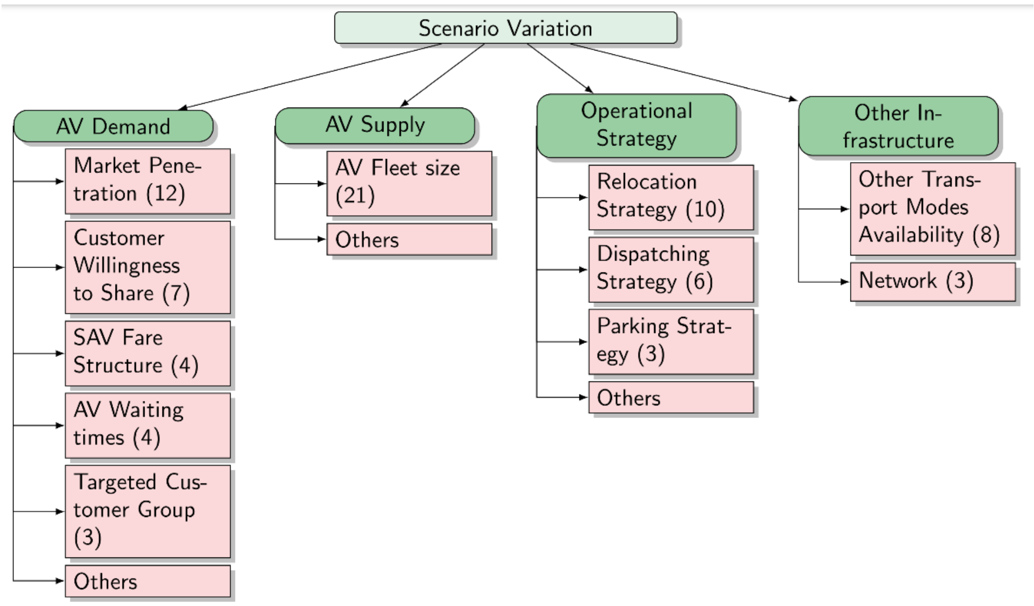

Figure 2.11: Factors for reviewed ABM scenario variations, 2021 review (Source: (Li et al., 2021)*)*

Simulation output and result analysis

When it comes to AVs, the most common question is how many standard vehicles can they replace, and the number varies depending on the mode of operation. Different research can present different values, but generally speaking, SAVs can replace from 4 to 10 standard vehicles, depending on many factors. Although, some research have reached results with even higher vehicle replacement ratios, such as 1:14 in a hypothetical city case study. Considering a more optimal scenario in which an SAV can replace about 10 standard vehicles, this would mean a 90% reduction of not only the number of vehicles present in the network, but also of parking needs, leading to land-use savings. It is worth noting that, without SAVs, the capacity improvement of private AVs is somewhat limited. Additionally, despite the replacement rate being high, it does not necessarily mean that the network will not be congested, since studies typically show a VMT/VKT rise of about 20%, which means that the network will have approximately 1.2 times the original traffic. As mentioned, there are many factors that can significantly impact the fleet size or replacement rate, some of the most common include: AV market penetration, service area (and respective network shape), average demand, ride sharing, trip flow density, average waiting time, expected service level, ride sharing, relocation strategy, and targeted user groups. (Jing et al., 2020; Li et al., 2021; Zhang et al., 2015)

In terms of simulation output indicators, the most frequent (according to the 2020 systematic review) are the following: indicators related to time (which are divided into, by order of frequency, waiting time, travel time, response time, service time), indicators related to distance, mode share, fleet size or replacement rate, cost analysis, service or rejection, parking demand and vehicle utilization (see Figure 2.12 and Figure 2.13). Note that although in Figure 2.12, fleet size is not presented as the most common indicator for the 2020 systematic review articles, we can verify that in Figure 2.9, fleet size appears as the most common variable, emphasizing its overall importance in these studies (Jing et al., 2020; Li et al., 2021).

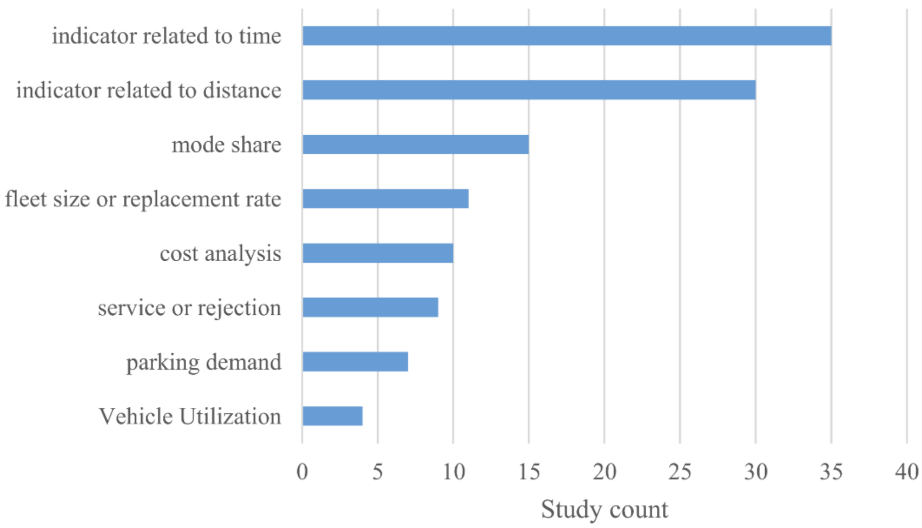

Figure 2.12: The main simulation output considered in the simulations, 2020 review (Source: (Jing et al., 2020)*)*

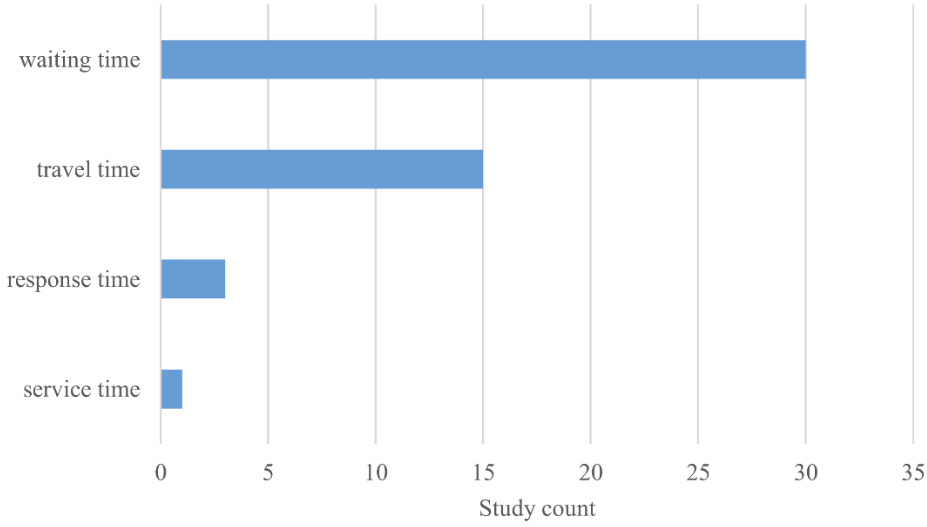

Figure 2.13: The indicator related to time - waiting time, travel time, response time, and service time, 2020 review (Source: (Jing et al., 2020)*)*

All these mentioned factors and indicators are important and influence significantly the outcome and result analysis of each simulation. The significance of their impact can be very high or simply not relevant, it will depend on each specific case and scenario, with many being interdependent. AV service level for example, is crucial for customer satisfaction, and depends strongly on the average waiting time (an average waiting time of 5 to 10 minutes can usually satisfy about 95% of travel demand). Passenger travel time and empty VMT/VKT are also service level characteristics. The use of electric cars could reduce service level of the system, due to vehicle range and charging time, although this is expected to be less of a problem with the advance of technology and can also be optimized in present day through the optimizing of charging schemes, additionally, there are strong environmental benefits associated with the use of SAEVs (Jing et al., 2020; Li et al., 2021).

Notwithstanding that private and ridesharing autonomous cars will bring multiple benefits, public transportation will still be very important, in particular in dense transport demand regions, since they have higher carrying capacity and a more efficient passenger/area ratio, as well as having lower fares (moreover, studies indicate that autonomous public transportation will be even cheaper than current prices) (Jing et al., 2020; Li et al., 2021).

2.2.3 Study Example

In this chapter, as already mentioned, we will take a quick overlook to a specific case study, the 2019 research article, “Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model”, published in the

Journal of Advanced Transportation, by Senlei Wang, Gonçalo Homem de Almeida Correia and Hai Xiang Lin (Wang et al., 2019). This study is useful as a guideline for the purpose of this thesis, with the software used in the study being the same (Anylogic) as the one used for the development of the present work.

Model specifications and operations

The ABM in this study was created to simulate the operation of SAVs in a parallel transit service (PTS) and a tailored time-varying transit service (TVTS), in which the latter can alternate between two service schemes: station-to-station service (SSS), also known as terminal-to-terminal, and door-to-door service (DDS), and the former permits the simultaneous operation of both SSS and DDS. Travel distance and price were not considered factors to guide user choice between the different services, instead, different levels of willingness to choose SSS in the PTS system were defined: PTS-20%, PTS-40%, PTS-60%, and PTS-80% (according to willingness to choose SSS). This willingness is assumed to differ according to price, or else clients would certainly choose DDS, since it is a more comfortable option (Wang et al., 2019).

In Figure 2.14 we can observe how the components of the system interact. Travel demand requests are met with the assignment of vehicles by the fleet operator in real-time. Once the vehicle has all the crucial data (origin, destination and identification) regarding the travel request, it will communicate with the requesters for pickups and drop-offs. In addition, the dynamic ridesharing module in the fleet operator will try to gather travelers together, and the routing module in the central traffic operator will then be responsible for generating a route in real-time for the assigned vehicle (Wang et al., 2019).

The authors considered the following model assumptions and specifications (Wang et al., 2019):

(i) No induced travel demand is taken into account
(ii) All the travelers are willing to share rides with strangers
(iii) The battery capacity can support full-day operations for each SAV
(iv) The parking spaces are enough for all the SAVs in each station;
(v) SAV speed is predefined on road segments and updated for peak hours and off-peak hours respectively;
(vi) Cancellation of assigned SAV is not allowed;
(vii) Travelers will give up a request when the waiting time for being assigned a vehicle exceeds a specific time threshold;
(viii) Travelers' choices between door-to-door service and station-based service are based on a fixed willingness to use a certain service, which is an experimental parameter (20%, 40%, 60%, and 80%).

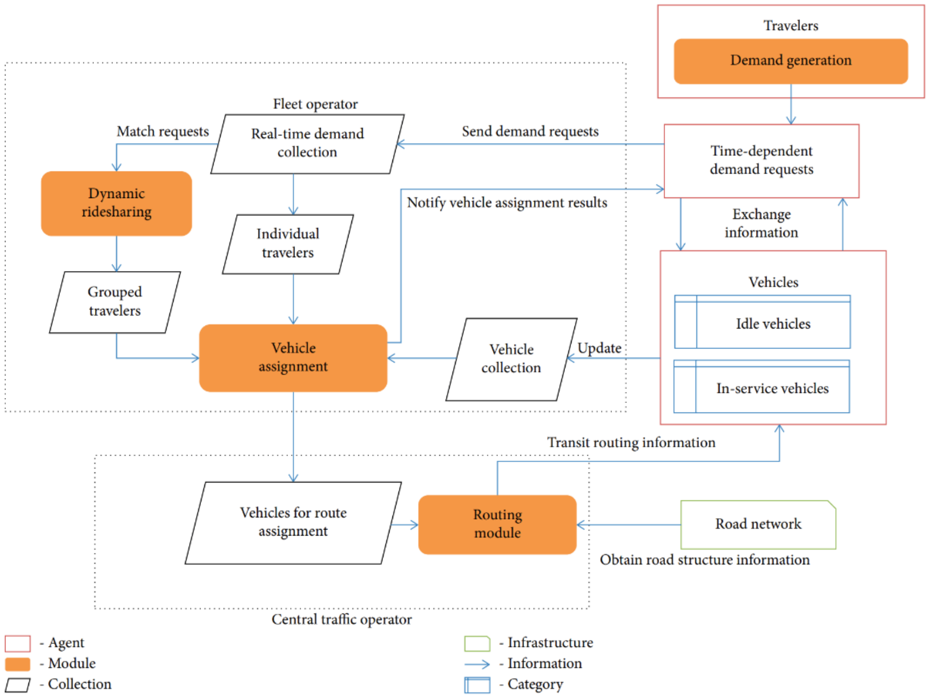

Figure 2.14: Interaction between system components of the study example (Source: (Wang et al., 2019)*)*

Two assignment techniques are developed in the model: the first-come, first-served (FCFS) assignment method, and an optimum assignment method. In the FCFS, the real-time demand request is met with the nearest idle vehicle, while in the optimal assignment method, a group of idle vehicles is assigned to a set of demand requests, with the goal of minimizing the empty VMT/VKT of the assignment (Wang et al., 2019).

The FCFS assignment method has the following straightforward rules (Wang et al., 2019):

(i) The fleet operator will find an idle and nearest SAV in the same sub-region as the request departure location based on the FCFS principle;
(ii) If there is no available SAV close to the request, the fleet operator will find an idle SAV from the whole study area to serve it;
(iii) The fleet operator only gives top priority to shared riders. That is, the travelers who will share their rides are sorted from the waiting list, and assigned an idle and nearest SAV as soon as possible.

As already mentioned, the fleet operator in the optimal vehicle assignment method can bundle requests and assign them to a set of idle vehicles (the size of the bundle will change according to the real-time demand), with the purpose of minimizing empty VMT/VKT. The matching problem between bundled requests and the selected set of available vehicles is solved using the Hungarian algorithm (the Hungarian algorithm method is an optimization algorithm that solves assignment problems). When the operator cannot allocate adequate idle vehicles to apply as input for the algorithm or there is only one request, the FCFS method applies (Kuhn, 2010; Wang et al., 2019).

The dynamic generation of demand is done by creating a specific number of time-dependent requests for each area and for a certain time period (spatial-temporal), and locating a destination for each request. In Figure 2.15, we can visualize the model's traveler behavior by means of a UML state machine (also known as state diagram or state chart). User-defined conditions (such as timeouts or rates, and agent's arrival) can prompt transitions (Wang et al., 2019).

The dynamic ridesharing intends to group several travelers with approximate spatial-temporal characteristics. Requests with matching OD regions can share an SAV. The authors used a defined set of rules for the implementation and function of dynamic ridesharing (these are described in the original article) (Wang et al., 2019).

Fleet size is an experimental factor in the model. Different fleet sizes are tested in the simulation, with size estimates being small, in order to maintain an adequate system service level (Wang et al., 2019).

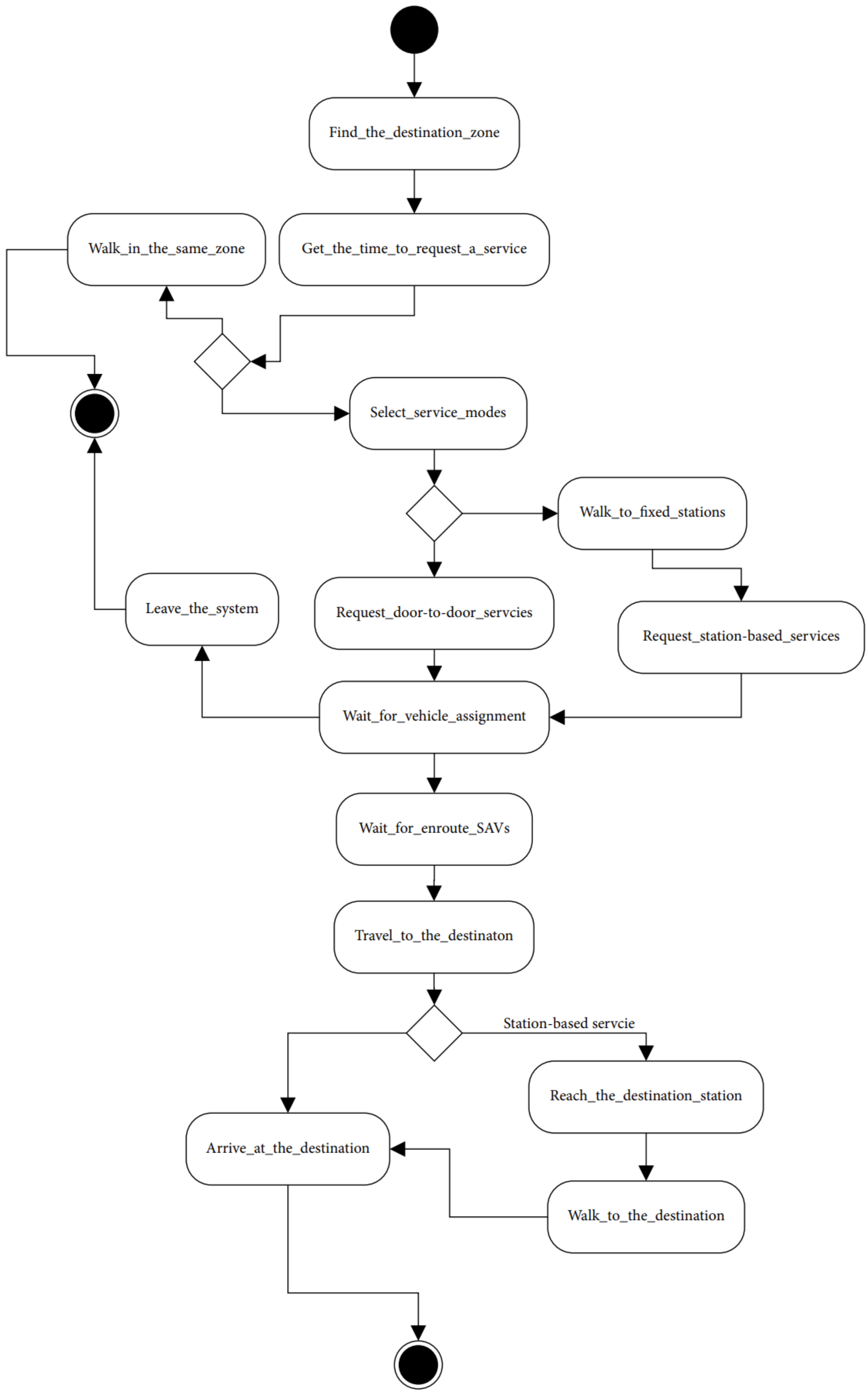

Figure 2.15: The state chart that represents the behavior of a travel request of the study example (Source: (Wang et al., 2019))

Model application and implementation

The model used for the simulation was created in the Anylogic software, more specifically in the Agent-Based Model platform, using Java programming language. Simulation tests were carried out in a hypothetical urban area, to test the presented SAV system and its different schemes. The road network of the hypothetical city (city scale of 5 km x 5 km) was obtained from the Urban Dynamics Education Simulator (UDES) model, and has 78 links and 77 nodes (Figure 2.16) (Wang et al., 2019).

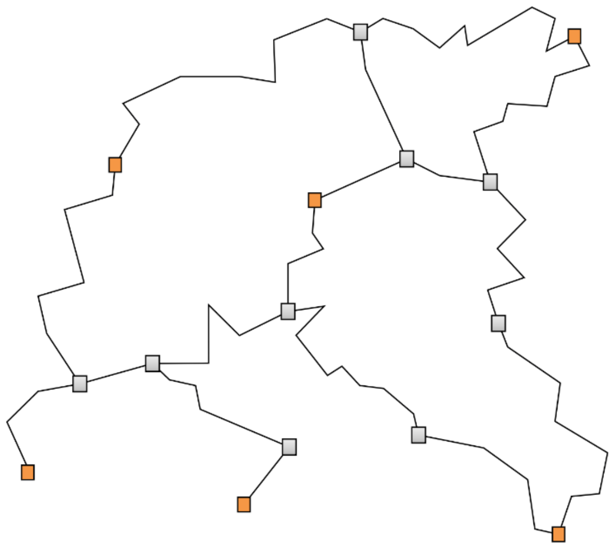

Figure 2.16: The road network of the study example (Source: (Wang et al., 2019)*)*

Figure 2.17 presents fundamental input parameters for the simulation. The system meets a total demand of 110,000 trips over a 24-hour period. The vehicle velocity is predefined for all systems and varies from peak hours to off-peak hours. In this model, a speed of 36 km/h is assumed for off-peak hours, with a 20% reduction in peak-hours. In terms of energy expenditure, a rate of 1 kWh per 7 km is assumed for a two-seat, lightweight car. The maximum waiting time before the client gives up is defined as 5 minutes. The adopted vehicle capacity for a shared vehicle is 2 passengers. And the time period for optimal assignment is 5 seconds (Wang et al., 2019).

TABLE 1: Input parameters.

Category	Value
City scale	5 km × 5 km
Road links	78
Road nodes	77
Travel requests	110 000
Vehicle off-peak speed	36 km/h
Vehicle peak-hour speed	28.8 km/h
Vehicle capacity	2 persons
Time threshold for client dropout	5 minutes
Time interval for optimal assignment	5 seconds
Operation hours	Around the clock
AM peak	7 AM–9 AM
PM peak	4 PM–6 PM
Fleet size	[2000, 4500]
Fleet size step	500

Figure 2.17: Input parameters of the study example (Source: (Wang et al., 2019)*)*

The results were analyzed in seven points (for a more detailed analysis of the results, see the original article) (Wang et al., 2019):

- Analysis of the Impact of Vehicle Assignment Methods
- Analysis of Fleet Size Variations
- Analysis of the Impact of Dynamic Ridesharing
- Analysis of Waiting Time and Service Time
- Analysis of VKT and Energy Consumption
- Analysis of System Capacity and Drop-Out Requests
- Analysis of Empty Trips

According to the results of the simulation, SAV systems combined with dynamic ridesharing can decrease average waiting time, VMT/VKT, and empty SAV trips considerably. Furthermore, the suggested optimum vehicle assignment method can minimize empty VMT/VKT for pickups by up to 40% for all assessed SAV systems and increase system capacity for passenger transportation. When comparing the TVTS system, which has inconvenient access during peak hours, to the PTS system, which always provides DDS, we find that PTS may achieve equivalent system performance in terms of average waiting time, service time, and system capacity as TVTS. Additionally, compared to the FCFS vehicle assignment method, the optimal assignment can lower empty VMT/VKT values for all analyzed systems and allow the SAV systems to transport significantly more clients (Wang et al., 2019).

2.3 Summary

Given the obvious potential of AVs, policymakers and the general public would be advised to pursue a smooth and well-planned introduction and transition to this new technology. With or without legislative and regulatory action, the state of AV technology appears to be improving. However, these initiatives will have a significant impact on how AV technologies evolve and are finally adopted. To solve the numerous challenges described above, intelligent planning, effective predictions, and regulatory action and change are necessary. Although there are enormous potential benefits, there are still significant challenges to complete implementation and widespread market penetration. Most people will be unable to pay the initial price of AV technology. Lawmakers and government institutions should start funding research into how autonomous cars could influence transportation and land use patterns, as well as how to effectively adapt our transportation system to maximize their advantages while avoiding any negative repercussions of the transition to a mostly self-driving fleet.

The concept of a self-driving car may seem far off, but autonomous technology is rapidly advancing, and certain capabilities are already available on current vehicle models. This new technology has the potential to minimize collisions, reduce congestion, increase fuel efficiency, reduce parking demands, provide mobility to individuals who are unable to drive, and transform the world's travel pattern drastically over time. These changes will have clear and quantifiable advantages.

Notwithstanding, in previous chapters, we talked about multiple potential benefits, regarding safety, congestion and traffic, travel-behavior, freight transportation and economic impact, but nonetheless, there are still some cons to these benefits. So, besides the previously exposed major issues concerning the implementation of AVs (vehicles costs, legislation and regulations, liability and ethics, security, privacy), we must consider these issues involving AV benefits' weaknesses. As long as humans travelling in a self-driving car have the option to shutdown self-driving mode and take control, many problems will persist, particularly in terms of safety. When a crash is inescapable, liability issues are a large concern and could be significant obstacle to implementation. The possibility of VMT increasing, may create further problems associated with high automotive use, like extra emissions, higher fuel consumption and more health issues. Already congested roadway infrastructure may be negatively impacted also due to the increase in trips. Urban sprawl will most likely increase with the implementation of AV, since commute time will be turned into useful time. The use of platooning with AV can create difficulties for other drivers trying to enter or exit highways, conceivably causing the need for new personalized infrastructure with dedicated lanes for platooning.

There are still many unknowns and the level of impact of all these underlying issues regarding the implementation of self-driving cars is difficult to estimate, mostly because we lack the data for that analysis. Tests and experiments have to be done, by using autonomous vehicles and AV fleets in various situations and scenarios, to collect the very needed data. But it will take some time for autonomous vehicles to be widely used in our daily lives, and operating an autonomous vehicle fleet can be quite expensive. This is where simulation systems come in. Simulation systems can be designed for the purpose of not only saving money but also to gather large amounts of data without having to use real-life vehicles in real-life scenarios, where the safety issues and legal constraints of field testing are a concern. Agent-Based Models are ideal for simulating AV systems, since they are better than the conventional methods of simulation in many aspects and simulate the model thoroughly from macroscopic to microscopic properties. An ABM uses interactions between its agents and environment to describe the system. In the case of an SAV system, it models travel demands and vehicle motion, and the interactions among travelers and vehicles. These simulated models can give us valuable information on how the elements of an SAV system interact and their various effects on the environment. This useful data can then be used to assist on decision taking, when implementing AV and SAV systems in real-life. Summarizing, simulations of AV and SAV systems through agent-based models are an important piece on the widespread adoption of autonomous vehicles. More data and studies translate in a quicker, proper and safer transition to a world where AV are the norm.

However, no matter how safe autonomous vehicles are and will eventually become, there will almost certainly be an initial sense that they are dangerous due to the lack of a human driver. Often, policy is driven by perception issues, which can cause implementation delays. But the reality is that humans are doomed to make mistakes. Even though we can improve and find better ways to do something, our capabilities are limited by many physical and biological factors. While the popular phrase “practice makes perfection” has some truth to it, there will always be some percentage of error and failure, and although it is true that machines have their share of error and failure, it is orders of magnitude lower than humans. We cannot compete with the precision and processing capacity of computers.

Consider the following example. An intersection in a certain city, full of cars with human drivers. The traffic light turns green, the first driver accelerates, then the second, then the third, and so forth, until someone must stop at the red light. If all the drivers accelerated at the same time, the individual that previously had to stop at the red light, would have gone through. Coordination is a major problem for traffic flow. Human drivers have slow reactions and short attention spans, and this limits how many vehicles can get through an intersection and can eventually lead to traffic congestion. This is the reason highways don’t have intersections. The more autonomous vehicles driving through an intersection (instead of human drivers), the more efficient it will get.

Nowadays, we already have self-driving cars on the roads, and in many places, you can turn on the auto-pilot and the car will drive itself, but the individual in the car has to be alert and ready to take over control at any given time and the individual behind the wheel is still legally responsible for what happens with the car (although, as mentioned in previous chapters, in some specific areas, there are already taxi services where the vehicle is fully autonomous with no one prepared to take over control). But in the following years, manufacturers of autonomous vehicles are going to take increasingly more responsibility for its actions. This has led people to consider ethics and moral problems when designing autonomous vehicles. We can think of basically infinite different scenarios where an autonomous vehicle would have to make a difficult choice, where it would have to choose between "the lesser of two evils" like steer into an old person instead of a pregnant woman, for example. But the fact is, accidents are taking place as you read this. Every year, more than a million people die and up to 50 million get injured on the roads, globally. And in more than 90% of these accidents, driver error is the problem. This is the true moral dilemma. Postponing autonomous vehicle implementation just because of a very small percentage of scenarios where a difficult choice has to be done, is getting distracted from the main issue. Each day we delay putting autonomous vehicles on the road, the more people will die and get injured. That should be the main moral and ethical question regarding self-driving cars, why aren't we putting them on our roads sooner.

The science communicator Derek Muller gives an interesting example: "(…) before the 1940s, almost all elevators had drivers in them (…) and when people started putting in driverless elevators, the public was very concerned and they didn't want to ride in those elevators. (…) Adoption was slow (…) they tried to advertise to help people understand that it was in fact safe, but ultimately, there was an elevator drivers' strike in New York City, and that really annoyed people, and it helped the adoption of automated elevators. If you found a driver in an elevator today, you would wonder "Why are they there?". Now you might think an elevator is just so simple (…) it is effectively one-dimensional motion. But airplanes are also flown extensively by computers. (…) humans are much more likely to take manual control and land on sunny days (…) the counterintuitive thing is that we expect the humans to be better, particularly in tough situations, but when it comes to airplanes, if it's bad weather, you actually want the plane flying itself. So, the obvious next question is, would you want the same thing for cars?" (Muller, 2021).

The most developed autonomous vehicles, such as Waymo fully autonomous vehicles and Tesla auto-pilot mode have more experience than any human driver, because they've accumulated data over millions of kilometers of driving on public roads. If you were an average driver, you would have to drive for hundreds of years to accumulate equivalent driving experience. Waymo has driven more than 20 million miles (32 million km) autonomously and has done more than 15 billion simulated miles (24 billion km) (Waymo, 2021). As of April 2020, Tesla has driven more than 3 billion miles (approximately 5 billion km) on auto-pilot mode (Trefis, 2020). In the 1st quarter of 2021, the Tesla Vehicle Safety Report states that "In the 1st quarter, we registered one accident for every 4.19 million miles driven in which drivers had Autopilot engaged. For those driving without Autopilot but with our active safety features, we registered one accident for every 2.05 million miles driven. For those driving without Autopilot and without our active safety features, we registered one accident for every 978 thousand miles driven. By comparison, NHTSA's most recent data shows that in the United States there is an automobile crash every 484,000 miles." (Tesla, 2021). Although, we should keep in mind that the driving environment where the majority of these Tesla auto-pilot miles were driven is not specified. The collected data is used to train the vehicle's systems, to improve the software, and the knowledge and experience gained can then be applied to the entire fleet. In Waymo's Safety Report, some types of accidents, like the car going off the road or hitting stationary objects, have been completely eliminated by the autonomous driving (Waymo, 2021). In the report, the eight types of significant accidents that happened with Waymo vehicles in over six million miles driving, involved a human driver doing something foolish, such as speeding, driving on the wrong side of the road, passing through a red light, etc.

Ultimately, autonomous vehicles do not need to be perfect and flawless, they just need to be better than us humans. And what many people are unaware of, is that they already are considerably better than the average driver. Self-driving vehicles are not something of the distant future, they are already here, and they work. The question is not, if autonomous vehicles will replace human drivers, but how quickly will this happen.

3 METHODOLOGY

3.1 Introduction

In this third chapter, we will explain the overall development of the simulation work, including model design, simplifications assumed, design and development within the simulation software, and post-simulation analysis approach.

The first step consisted in gathering data about daily trips within the Region of Coimbra in order to create an Origin/Destination Matrix. This was an easy step, since this data was already available, through a mobility inquiry done in 2009. The second step was a diagnosis of the region's mobility via an analysis of the data. In this analysis, we did multiple screenings of the trips until a final selection was reached. After having all the mobility data sorted out, we began developing the simulation model. For this task we resorted to the multimethod simulation modelling tool, AnyLogic. This software offers different options of simulation modelling, but in this work, we used an Agent-Based Model (ABM). In this type of simulation model, the actions and interactions of independent agents are simulated with the objective of evaluating their effects on the system as a whole (Anylogic, n.d.). After creating a general approach to the functioning of the model, we proceeded to implement it in the simulation software. First, we defined the physical space for the simulation, in our case, the road network of the Region of Coimbra. Then further work was done in many aspects, since we would be simulating the autonomous vehicle transport fleet providing door-to-door transportation to a number of generated users, and so there were many constraints and objectives to consider. In this step, the objective was to determine the number of vehicles in the fleet, assuming that all demand is satisfied. Initially, our plan was to consider three scenarios: time-shared scenario; time-shared and space-shared scenario; mixed case scenario. In the first scenario, only time-shared vehicles are considered. In this case, vehicles act similarly to a taxi service, making direct connections between origin and destinations, and one person per vehicle is assumed. In the second scenario, in addition to being time-shared, the vehicles are also space-shared, similar to a shuttle service. This means that ridesharing is possible, and detours can be made in order to pick up passengers, thus, predictably, most vehicles would have multiple passengers travelling at the same time. Note that this does not mean that there would always be more than one passenger in the car, there can be moments where the car only has one passenger or none. In the third and last scenario, some mixed case scenarios are considered, where, contrary to the previous case, a certain percentage of cars serve strictly as time-sharing and the rest serve as both time and space-sharing vehicles. However, due to time restrictions, we only considered a time-shared scenario (this will be further explained in future chapters). We did not consider the existence of private vehicles, since the fleet satisfied all mobility demand for the region and all fleet vehicles were shared by the users. The last step of model development served to introduce the electric functioning component to the vehicles and determine the number of charging stations and where they should be located. Initially, this was planned to be achieved on the basis of already having calculated the number of vehicles for the fleet (previous stage). But, as later will be explained, another approach was chosen, with the number of charging ports being calculated in the same simulation as the previous stage.

3.2 General Procedure

Before starting to build the model in the simulation software, we needed to outline the general procedure for how the model would work. As mentioned previously, although ridesharing is a key element for this work and project, it was not fully employed in the simulation due to time restrictions for both development and simulation. The vehicles in the simulation are still time-shared, but not space-shared, that is, the same vehicle can be used by different travelers at different times, but travelers cannot share the vehicle at the same time (ridesharing is not allowed). Nonetheless, we idealized a model design that is able to accommodate ridesharing (see Figure 3.1). In this model, there are two main input variables: maximum waiting time and maximum trip added time.

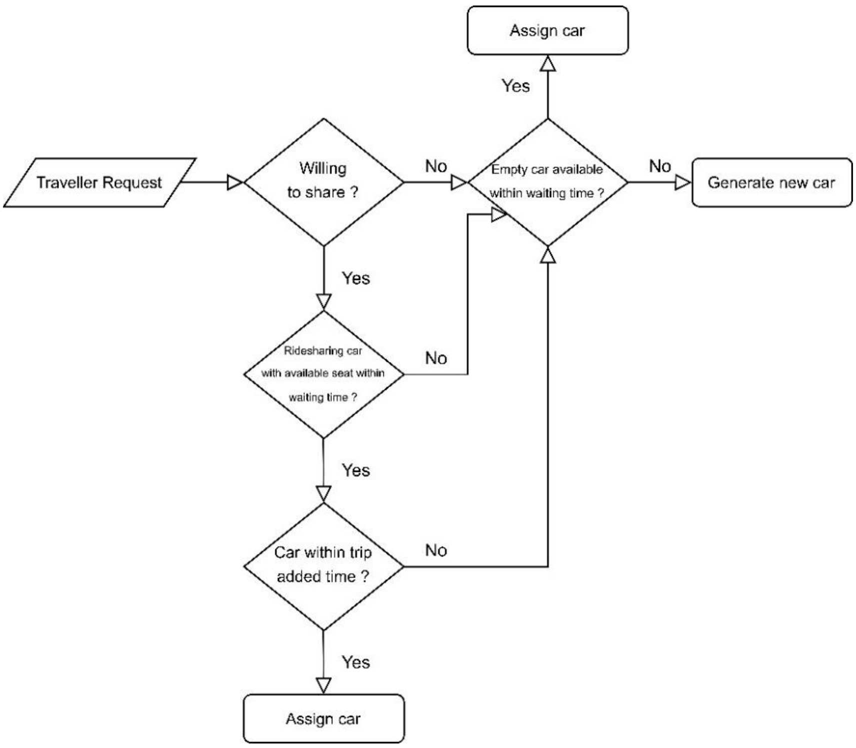

Figure 3.1: Ridesharing (time and space) model flowchart

Following the flowchart in Figure 3.1, firstly there is a travel request in the system. The traveler may be willing to share the vehicle (rideshare) or not, that is, he may be willing to travel with another traveler in the vehicle simultaneously and possibly having a certain added time to his original trip duration. This willing to share is normally associated with a financial benefit opposed to not sharing, i.e., the traveler's will to share may be influenced by the lower fare of a shared vehicle. If the traveler is willing to share, then the system operator will search for an existing nearby ridesharing car (that is, a vehicle that has a current traveler willing to share) with an available seat that is within the new traveler's maximum waiting time and within the maximum trip added time for both the current traveler and the new traveler. If the vehicle in question meets these criteria, then it is assigned to the new traveler, and the vehicle will make a detour to stop and pick up the new traveler. If one of these criteria is not met or the traveler is not willing to share, then the system operator will search for an existing nearby empty car that is within the new traveler's maximum waiting time. If a vehicle is available, then it is assigned to the new traveler and will drive to the traveler's location and pick him up. If no vehicle is available, the system will generate a new car to meet the demand. This new car is added to the existing and active vehicle fleet.

The model that was actually used in the simulation software does not include rideshare, and, therefore, is a simplification of the previous model (see Figure 3.2).

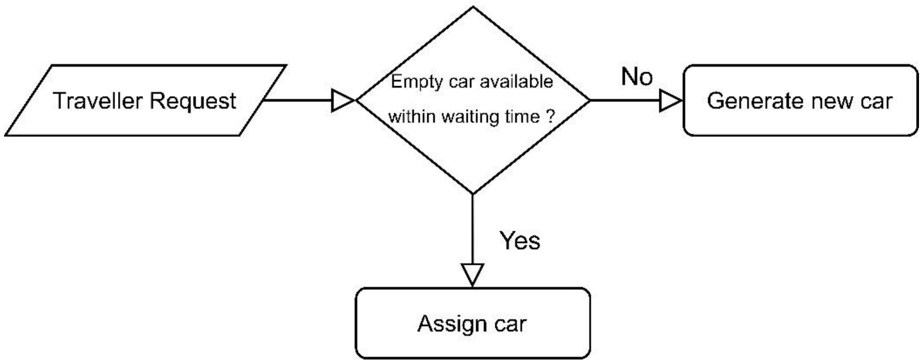

Figure 3.2: Ridesharing (time only) model flowchart

Following the flowchart in Figure 3.2, firstly there is a travel request in the system. The system operator will search for an existing nearby empty car that is within the new traveler's maximum waiting time. If a vehicle is available, then it is assigned to the new traveler and will drive to the traveler's location and pick him up. If no vehicle is available, the system will generate a new car to meet the demand. This new car is added to the existing and active vehicle fleet.

3.3 Model Development

For the software model development, we were provided with a license to use the AnyLogic 8.5.2 University version from 2019. As mentioned previously, ridesharing is not considered, so the simulation model developed is based on the flowchart model design from Figure 3.2. Notwithstanding, the model was built in such a way, that the ridesharing function could be enabled later on (for future research purposes) (Anylogic, n.d.).

3.3.1 Waiting time

As seen by reviewing the literature, waiting time is an important factor of both input and output information when simulating a transport service. In this model, it is a key parameter, more specifically, we input the maximum waiting time desired, before running the simulation. In order to ensure a good service level, most ABM studies define a maximum waiting time anywhere from 5 to 20 minutes, although some studies have an indefinite maximum waiting time (Jing et al., 2020; Li et al., 2021). On a psychological level, we verify that these values are somewhat acceptable. Without getting to much into the psychological side of the perception of waiting time, in a study from 2019 regarding the acceptable wait times at transit bus stops, survey results indicated that the least acceptable wait time beyond the scheduled arrival time reported was 1 minute and the maximum acceptable wait time was 20 minutes, but most users' acceptable wait times ranged between 5 to 15 minutes (Arhin et al., 2019). User's average wait times varied depending on a number of factors, such as time of day, presence of bench, gender, ethnicity and knowledge of bus arrival time. Although this mentioned study can give us a reference values for the acceptable maximum waiting times, it is not directly comparable to this work, since in the study, the analyzed acceptable wait time is a delay time beyond what was scheduled. In this work, the traveler would be given an estimated waiting time (such as when you order an Uber for example) based on the ETA (Estimated Time of Arrival) of the vehicle to his location. This is different in the sense that, when you request a vehicle, you will then be informed of the ETA, and only have to be ready at the pickup location at that time (for example, a certain person is working and will be ready to go home in about 10 minutes, the person could request a vehicle in advance, so that when they are ready to go home, the vehicle is already arriving, avoiding the need to wait at all). In the "The Psychology of Waiting Lines", by David H. Maister, the author states that "Waiting in ignorance creates a feeling of powerlessness, which frequently results in visible irritation and rudeness on the part of customers" (Maister, 1985). So, the fact that the traveler knows in advance how much time they will have to wait, allows us to stretch the waiting time range, while maintaining a good service level perception to most of the user population.

3.3.2 Battery capacity, consumption and charging

Since the model uses hypothetical future vehicles, some assumptions needed to be done regarding the vehicle technology. In this case study we tried to find a balance between future and present technology. It is well known that, with time, technology gets better and production costs lower, making it more accessible to the general public. Autonomous vehicle technology, batteries, engine efficiency, etc., follow this trend. This said, regarding both the vehicle's battery and energy consumption, we opted for values that are above and below average, respectively. We assumed a battery capacity of 100 kWh. This battery capacity is above the approximately 59 kWh battery capacity average of the many already available commercial electric vehicles, with some models actually surpassing 100 kWh battery capacity. Having a smaller battery usually means less range, but it also means the car is lighter, so energy consumption won't be as high, and thus there is some increase in range (nonetheless, in general, having a larger battery will translate in more range). Although not considered in this work, charging the vehicle can possibly be associated with solar panels, as some manufacturers are already doing, increasing the vehicle's range. In terms of energy consumption, we assumed 100 Wh/km at a speed of 10 m/s (36 km/h), with the rate of energy consumption varying according to the vehicle's speed (Equation 3.1), thus, the energy consumption of the vehicle's battery depends on how much distance and how fast it drives. The energy consumption increases linearly with the vehicle's speed, i.e., higher velocities mean higher battery expenditure (and thus less range) and vice-versa. This energy consumption per kilometer is almost half of the current average of 195 Wh/km. Although this is a big leap, we have to remember that this study is for a future vehicle fleet, and technology will be further along then. Notwithstanding, there are already electric cars that can average this value of energy consumption or even less, mostly prototype vehicles and vehicles involved in research, but even some soon to be available commercial vehicles get close to this value (for example, the available for pre-order electric vehicle "Lightyear One" has an estimated energy consumption of 104 Wh/km). In summary, these assumed values appear to be reasonable, even for present technology standards (Electric Vehicle Database, n.d.-a, n.d.-d, n.d.-b; Lightyear One, n.d.; Lu et al., 2014; Ribau et al., 2012).

$$Energy\ consumed = 100 \times \frac{v}{10}\ [Wh/km] \qquad , where\ v\ is\ the\ vehicle\ speed\ in\ m/s \tag{3.1}$$

Regarding the charging stations, it was assumed the existence of charging stations in every zone, with the number of ports varying from zone to zone, depending on the demand. Another approach could have been creating fewer charging stations and locating them in the surroundings of the more urban areas. In practical terms, this may be the best approach (depending on each case), to avoid the need of dedicated parking space in the central urban areas. Nevertheless, in this case study, we did not consider this approach in the simulation, since obtaining an optimal location would further strain the already slow running simulation. An optimization process could have been applied to the simulation results to find the ideal number of charging stations and their respective location, which is normally associated with vehicle parking. But this would mean having to develop an optimization model, which is not the purpose of this work (another work is being developed within the Driving2Driverless project to determine the ideal locations for parking the vehicle fleet). In this work we used a simplified process consisting of charging the vehicles where they were parked in each zone. For the charger's capacity, we assumed supercharger type characteristics, that completely charge the 100-kWh battery in one hour (as mentioned in the Introduction, when the topic of Electric Vehicles was addressed), presently there are already chargers with this kind of capacity, with many currently available superchargers already charging these kinds of capacities in less time).

3.3.3 AnyLogic Model Interface

Three types of agents were created in the ABM simulation model: cars, travelers and zones. Each type of agent has parameters, variables and functions associated with them. The AnyLogic software main window, in Figure 3.3, contains the parameters, variables and functions relevant to the model. It is in this window that we have the GIS (Geographic Information System) map, where the agents coexist and interact. The GIS map is an AnyLogic available tool that allows us to display and manage GIS maps in the model. This GIS map in specific, is what is called a tiled map, that is transferred in real time from online map services (for example, OpenStreetMap). It precisely represents the real terrain and road network of the region. The OD zones have geographic coordinates, which are placed in this map accordingly. Traveler agents will generate at certain locations according to the OD table and request a vehicle. Car agents will then be generated and drive through the road network in the map. This process can actually be visualized during the simulation (although this option was later turned off to ease the amount of software processing). The simulated day was defined as 90 thousand seconds (25 hours) long, so that travelers that start their trip late in the day (trip requests are only generated from the beginning of day until midnight) could have to time to get to their location and finish the trip. Since we only simulated one day, we assumed that all vehicles would be generated with 50% battery charge level (and could later charge to 100% when needed).

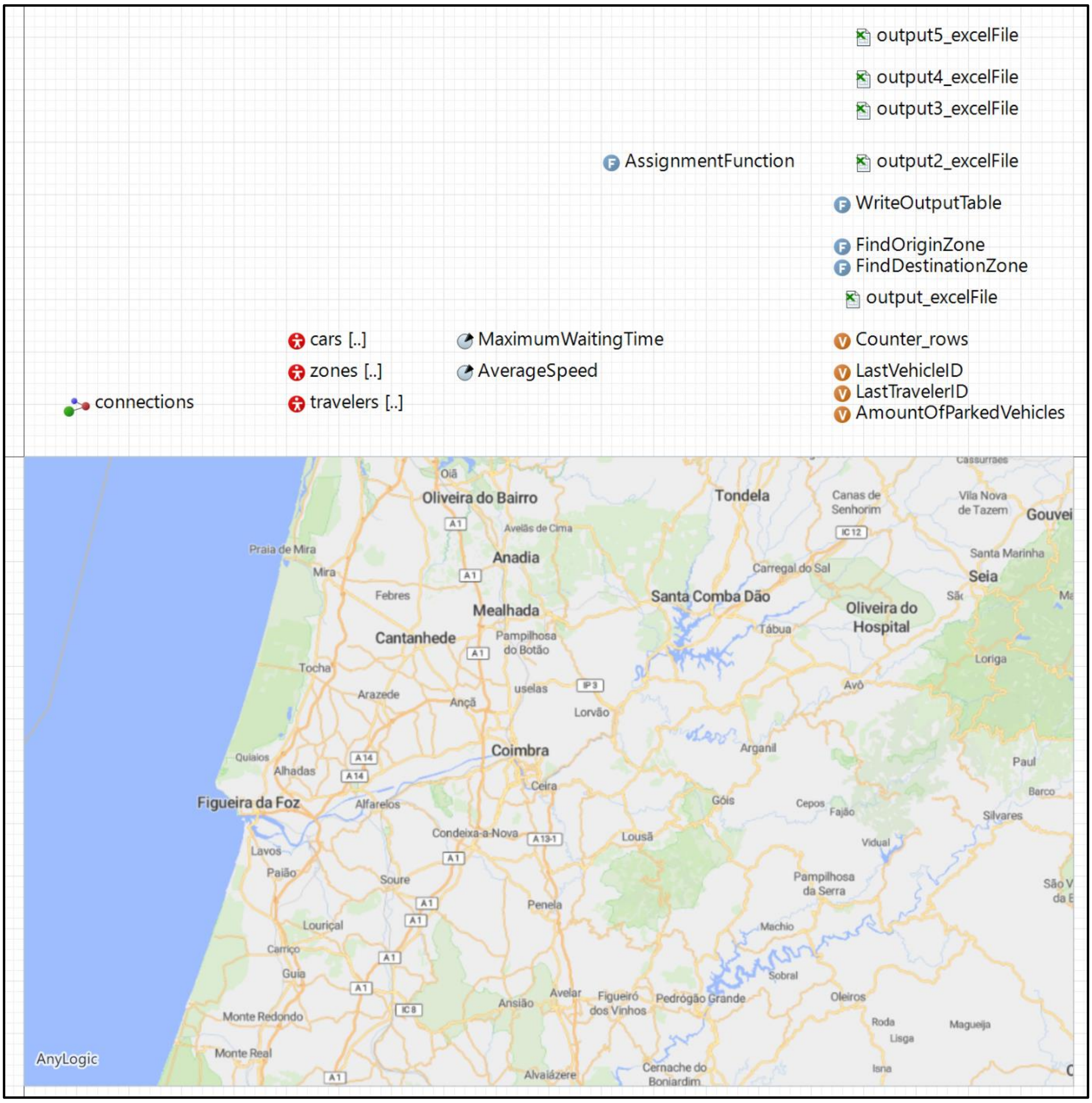

Figure 3.3: Print from the AnyLogic software, showing the main window of the model (parameter: ; variable: ; function: ; agents:)

In the Zone agent window (see Figure 3.4), we have the following parameters: ID, Name, Longitude, Latitude and Population. For each zone, these parameters are linked to the input from the Attribute Table. There are also two variables, one registers the total number of charges made in each zone, and the other counts the number of cars that are currently charging in each zone, during the simulation (this last variable is associated to a data set tool, that registers the value of the variable every 60 seconds, giving us data on how the number of simultaneous charges, in each zone, varies along the day). At the end of the simulation, for each zone, these values will be registered as an output.

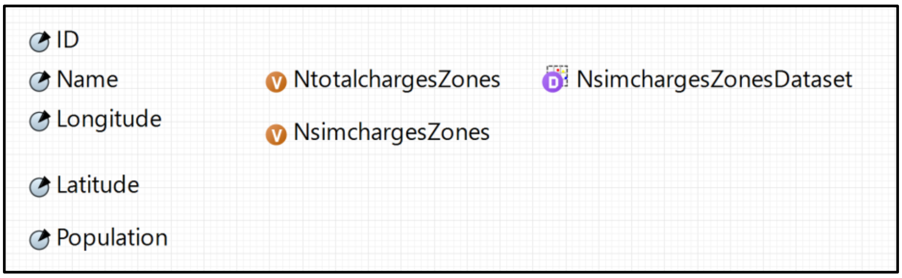

Figure 3.4: Print from the AnyLogic software, showing the Zone agent window of the model (parameter: ; variable:)

In the Traveler agent window (see Figure 3.5), we have the following parameters: ID, Origin (origin zone ID), Origin name (origin zone name), Destination (destination zone ID), Destination Name (destination zone name), Departure Time, and Expected Travel Time. As before, these parameters are linked to the input data, from the OD table. Multiple variables related to actions such as measuring waiting time, travel time, travel distance, and calculating expected waiting time, are associated to this agent. But more importantly, in this window we have the traveler statechart. This statechart defines how the traveler agent exists within the simulation. All traveler agents are generated from the OD table at the beginning of the simulation and will immediately become idle (their state will be "Idle"). Note that, although it may seem counterintuitive to generate all agents at once in the beginning of the simulation, it is indeed beneficial regarding simulation running time, since reading or writing data during the simulation, opposed to at the start or at the end, dramatically increases running time; this type of approach was actually tried out during the model development, in an effort to decrease running time. As the simulation is running, at each agent's departure time, the agent will become active and enter the "Waiting for Assignment" state. In this state, the waiting time started counting and the vehicle assignment function was called from the main window, which in turn will call the vehicle searching function from the traveler window. This second function searches for an existing vehicle within the defined maximum waiting time by calculating how much time will a parked or moving vehicle take to arrive to the traveler's location (in the case of the moving vehicle, it will calculate how much trip time the vehicle has left with its current traveler and sum the trip time from its current traveler destination location to its new traveler origin location). Due to the software's limitation, it is not possible to calculate exactly how much time a vehicle will take to arrive through the map, so these trip times are provided as input (Expected Travel Time). In a minority of cases, the traveler's waiting time will actually surpass the defined maximum. If there are no available vehicles that meet the criteria, then the vehicle assignment function will generate a new car to meet the travel demand and assign it to the traveler. A message will then be sent to the traveler, informing that a vehicle has been assigned to him and will pick him up. The traveler will now enter the “Waiting for Pick Up” state and maintain it until it receives a message informing that the vehicle has arrived. At this point, the traveler will enter the “In Movement” state, and the waiting time will stop counting and be stored as a variable, to be registered later, as an output. When the vehicle arrives to the traveler’s destination, it will send a message to the traveler informing he has arrived and he can now enter his final state, where he ceases to be active. At the end of the simulation, for each traveler agent, values such as Traveler ID, Origin, Destination, Departure Time, Traveler Waiting Time, Traveler Assigned Time and Traveler Travel Time will be also registered as an output.

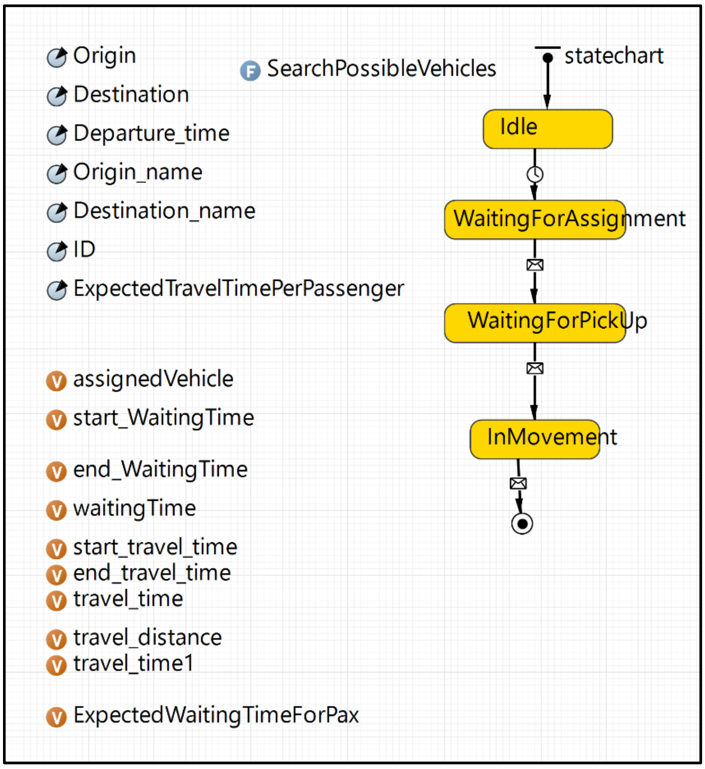

Figure 3.5: Print from the AnyLogic software, showing the Traveler agent window of the model (parameter: ; variable: ; function:)

In the Car agent window (see Figure 3.6), we only have one main parameter, the car ID (which is defined by order of being generated). The main variables associated with this agent are related to actions such as, counting the number of trips and charges for each vehicle, giving the value of each vehicle’s current zone ID and assigned traveler ID. In this window, we have both a statechart (yellow rectangles) and three system dynamics charts (light blue rectangles). Just as before, the statechart defines how the agent exists within the simulation. When generated (since we only simulated one day, we assumed that all vehicles would be generated with 50% battery charge level and could later charge to 100% when needed), car agents will be parked at the traveler's request origin location coordinates (their state will be "Parked"), but since they are generated to serve a travel request message, they will immediately change to the state "Waiting for Passenger", send a message to the traveler informing the vehicle has arrived, and the Current Zone variable value will be set equal to the assigned traveler's origin zone ID. In the case that the assigned vehicle was already previously generated, thus, was assigned to a traveler that was within the defined maximum waiting time, the car agent will change to the state "Moving to Pick Up" and proceed to move to the assigned traveler's location coordinates. When the agent arrives to the traveler's origin location, a message will be sent to the traveler informing the vehicle has arrived, the car agent will change to the state "Waiting for Passenger" and the Current Zone variable will be set to the assigned traveler's origin zone ID. When the traveler agent gets into the car agent, the vehicle will then change to the state "Moving to Drop Off" and proceed to move to the traveler's destination location coordinates. When entering this state, the simulator will also start counting the assigned traveler's travel time. When exiting this state, the travel time will stop counting and be stored as a variable, to be registered later, as an output. In addition to that, the variable that counts the vehicle's number of trips will increase by one, and the Current Zone variable will be set to the assigned traveler's destination zone ID. At destination arrival, the traveler will leave the car, and the vehicle can now take one of three options: park, charge or pick up another traveler. If the battery level is 30% or higher and there is a travel request within the maximum waiting time radius, the vehicle will immediately move to pick up this new traveler (change to the "Moving to Pick Up" state). If the battery level is 30% or higher and there isn't any travel request that meets the criteria, the vehicle will park (change to "Parked" state). Finally, if the battery level is below 30% of its capacity (this battery capacity level is about enough to make any given trip within the Coimbra region) the car will go to a charging port (change to the "Charging" state), fully charge its battery and then move to the "Parked" state. In the "Parked" state, if the vehicle's battery level is below 90% and within 30 minutes there is no new travel request for the vehicle, i.e., if the vehicle is parked for more than 30 consecutive minutes, the vehicle will go to the charging port (change to the "Charging" state) to fully charge its battery and then return to the "Parked" state. Regarding the system dynamics charts, each one has a different purpose (identically to the statecharts, these charts function independently for each car agent in the simulation). One controls the battery level, by having both a charging flow and consumption flow (these rates were mentioned above). The other two register the car's total distance driven (in meters) and the total energy used (in kWh), respectively. At the end of the simulation, for each car, values such as Car ID, Number of Trips, Number of Charges, Current Zone ID, Energy Used and Distance Driven will be registered as an output. It should be noted, that initially, the simulation model was also registering all sorts of live data, during each vehicle's trip, but in order to simplify the amount of software processing, this data registration was disabled.

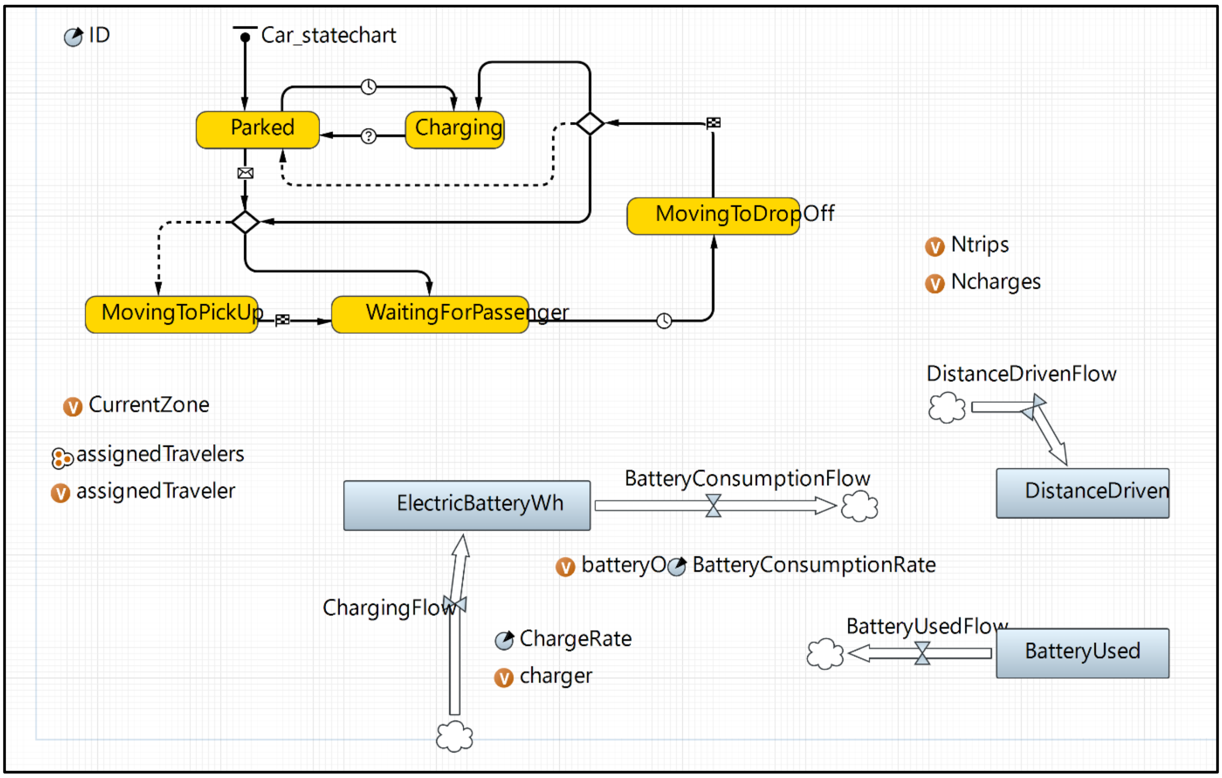

Figure 3.6: Print from the AnyLogic software, showing the Car agent window of the model (parameter: ; variable:)

3.3.4 Software and Model Limitations

After the simulation model was functioning and ready to run, it was then time to start running multiple simulations to obtain result data. Since the quantity of input data was too big for the software to handle in feasible time (a software limitation, since the computers used were not using their hardware capacities at the limit - most of the time, memory usage was 2-3% of what was available), several attempts were made to reduce the running time by downsizing the total travel demand. After testing all the total travel demand size samples mentioned in Section 4.2.4, we reached the conclusion that the only samples running in a feasible time were the sizes 10 and 20 times smaller than the full size. The 10 times smaller size sample took more than 9 days to complete one simulation. Though, due to time restrictions and the instability of the AnyLogic software (with frequent crashes), we used the 20 times smaller size sample, that took approximately 4 days to complete a simulation. As mentioned before, this downsize came at a cost, with the different trips becoming disproportional and less representative of reality.

Based on what was stated above, one of the things done to speed up the simulation time, was turning off the OpenStreetMap server vehicle routing, so the software would instead use straight-line distance. This too came at a cost, since the straight-line distance is lower than the real road distance, and travel time was predefined, the vehicle had to lower its speed in order to complete the trip in the determined time (less distance to cover in the same travel time, thus, slower speed). In addition, as mentioned before (Section 3.3.2), the battery's energy consumption rate depends on both the vehicle's speed and distance covered, so the energy consumption rate was quite lower than what it should've been.

3.4 Post-simulation Analysis

The output data retrieved from the simulations is then sorted out and processed. The main output variable is the vehicle fleet size. The fleet size varies with the defined maximum waiting time (see Figure 5.4). So, from the multiple simulations done, we are able to trace a trend line that represents how the fleet size varies with the maximum waiting time.

The total of charges done in each zone during the simulation and how many cars were charging at the same time at any given time are stored during the simulation. This allows to determine, for each zone, how much energy is needed to charge the vehicles and the number of charging ports needed. Other types of statistical data (although more limited in quantity than what was planned, due to the stated issues) such as distance driven, energy used (per vehicle), number of trips (per vehicle), average traveler waiting time and others, were also registered and analyzed.

Note that, if simulation was run with the complete ridesharing model, the vehicle fleet size would vary according to maximum waiting time and maximum trip added time. In that case it would be necessary to do combinations of different values for both parameters and the number of simulations needed would be squared. The result would be a trend space-curve. In addition to that, if we also assumed multiple scenarios with different penetration rates, we would have multiple trend space-curves as a result, that could then be compared.

4 CASE STUDY

4.1 Introduction

As already mentioned, this work focus on the design of an SAEV transport service through simulation, for the Region of Coimbra (NUTS III), in Portugal. The "Comunidade Intermunicipal da Região de Coimbra" (Intercity Community of the Region of Coimbra), or simply "Região de Coimbra" (Region of Coimbra) is a Portuguese administrative division, more specifically, a NUTS III subregion of the "Região do Centro" (Centro Region). The intercity community is composed of 19 municipalities (see Figure 4.1), which are then subdivided into "Freguesias" ("Freguesias", usually translated as civil parishes, are a third-level Portuguese administrative subdivision): Arganil, Cantanhede, Coimbra, Condeixa-a-Nova, Figueira da Foz, Góis, Lousã, Mealhada, Mira, Miranda do Corvo, Montemor-o-Velho, Mortágua, Oliveira do Hospital, Pampilhosa da Serra, Penacova, Penela, Soure, Tábua and Vila Nova de Poiares, incorporated under Law No. 75/2013, of 12 September (*Lei Nº 75/2013, de 12 de Setembro*, 2013), with Coimbra being its main city. The Region of Coimbra is similar to the administrative division of the District of Coimbra, with the difference being that the intercity community also includes Mealhada (from the District of Aveiro) and Mortágua (from the District of Viseu). According to the 2021 census' preliminary results (see Figure 4.2), the Region of Coimbra has a total population of 436 949 (5% less compared to 2011). The total area is 4,336 km^2 and the population density is about 101 individuals per square km (CIM RC, n.d.; *Lei Nº 75/2013, de 12 de Setembro*, 2013; Gabinete de Estratégia e Estudos, 2019; INE, 2021).

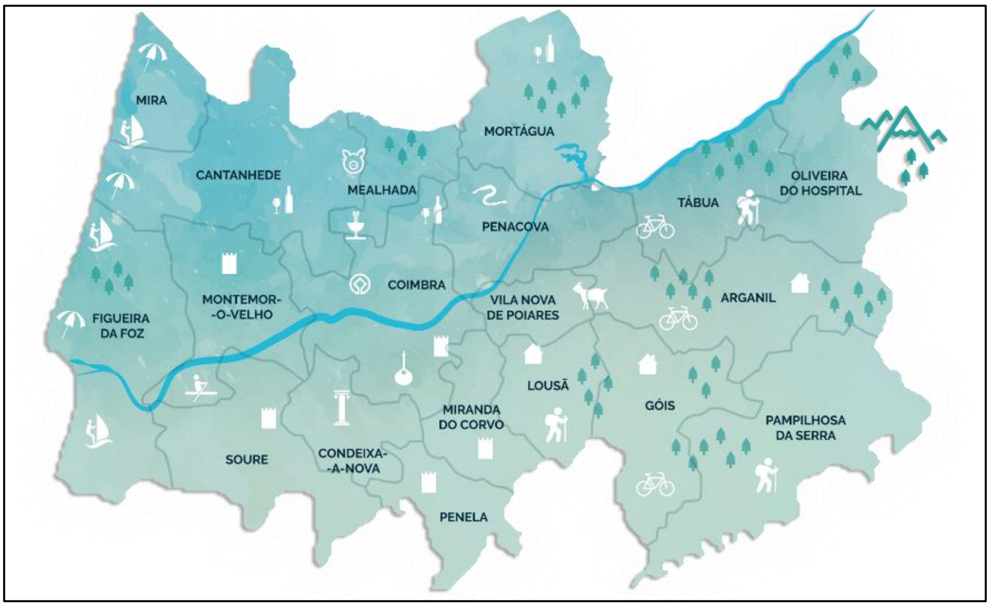

Figure 4.1: The 19 municipalities of the Region of Coimbra (Source: (CIM RC, n.d.)*)*

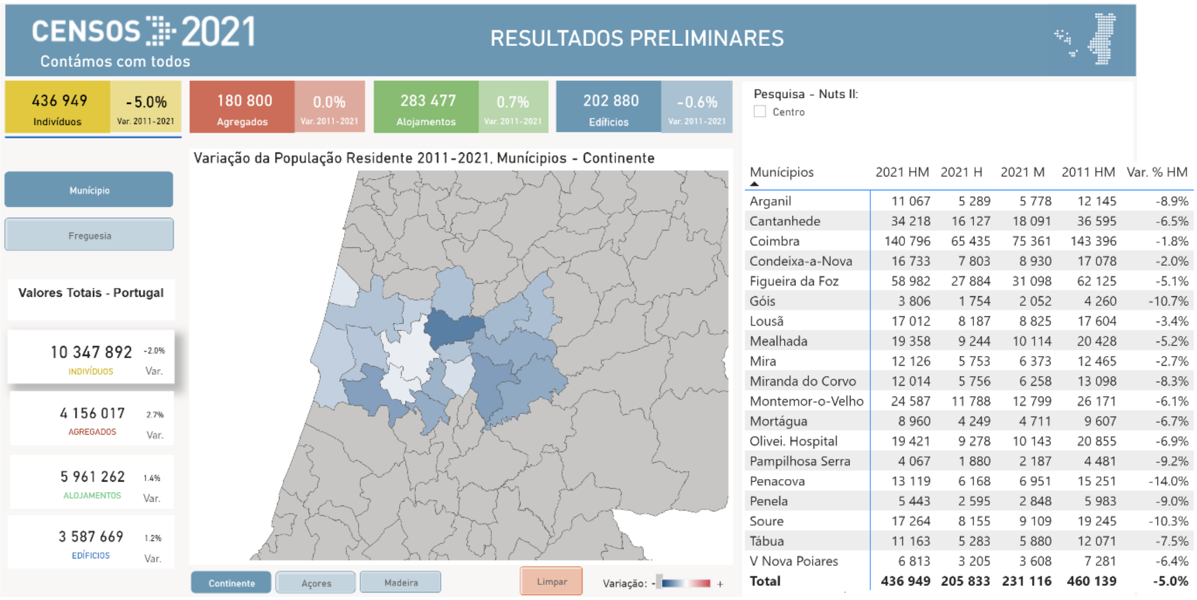

Figure 4.2: Adapted print from the 2021 Portuguese census website regarding population data from the municipalities of the Region of Coimbra (Source: (INE, 2021)*)*

For the mobility analysis of this region, we were provided with data from the mobility inquiry report (TIS, 2009) (this inquiry was done with the purpose of acquiring data for the project "Metro Mondego", which had the goal of constructing a network of a light surface metro to operate within some areas of the region of Coimbra). In this mobility inquiry, zones of origin and destination were created either by aggregating parishes (particularly in rural areas) or by subdividing parishes (particularly in urban areas). In this work, we considered the same zone divisions as in the mobility inquiry report (see Figure 4.3) for our trip data (in both boundaries and identification number).

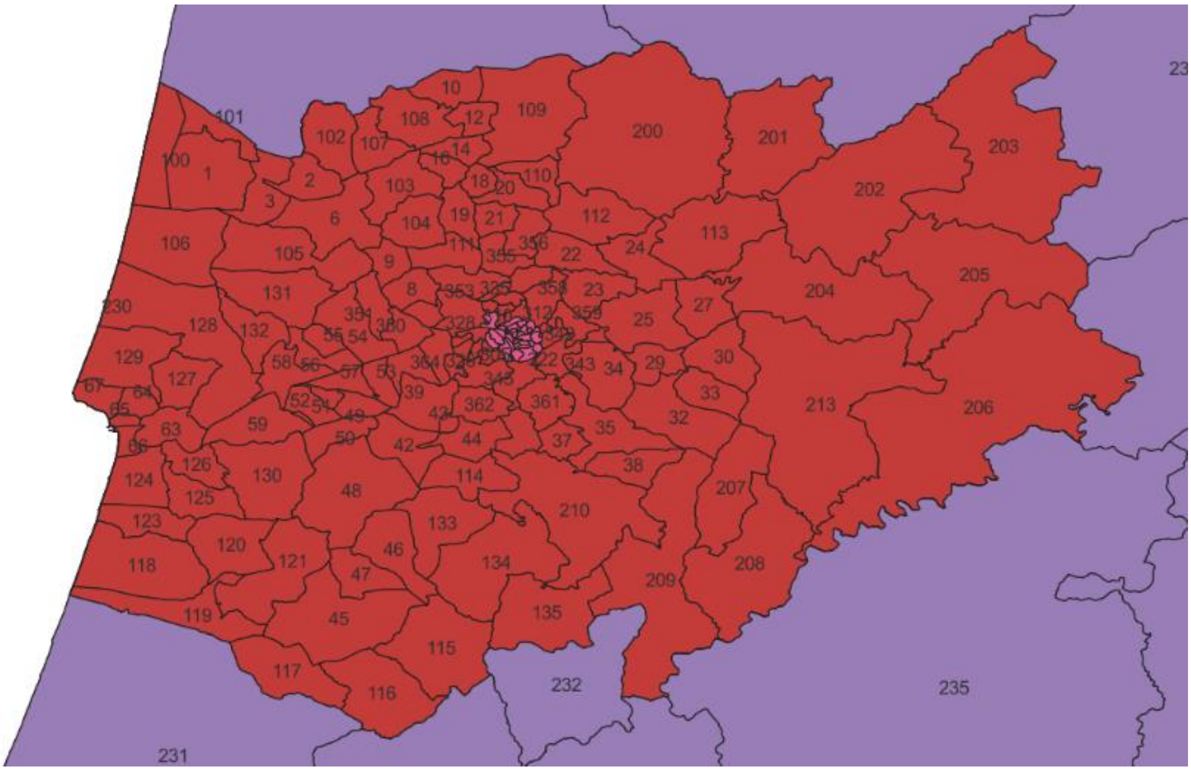

Figure 4.3: Print from the QGIS software, showing Mondego mobility inquiry report's zones

For the purpose of this study, trips inside the zones and from or to zones outside the region of Coimbra were discarded, since the main objective of this transport system is to serve trips within the region of Coimbra. Note, that in Figure 4.3, we are seeing all the internal covered zones in the inquiry (zones with red color and zones with pink color), which includes the entire Region of Coimbra (NUTS III), plus some additional areas, that belong to other intercity communities (note that, the pink colored zones correspond approximately to Coimbra's urban perimeter). In this study, we only consider zones that are within the intercity community of Coimbra, thus, some of the represented zones in Figure 4.3 are not part of this study.

The Table A.1 in the Appendix shows the zones considered (and their respective population), which act as origin and destinations for the trips. As mentioned, these zones have the same boundaries and are numbered as they were in the Mondego mobility inquiry report (TIS, 2009).

4.2 Case Study Data Processing

4.2.1 Population variation and assumptions

In the report, they use population data from the 2001 census as a basis and estimate a population size for each zone in 2009. Nowadays, we have more recent data regarding population size, more specifically, from the 2021 census. By obtaining the preliminary results from the 2021 census, we can compare and see how the population has changed within the region of Coimbra. Table 4.1 shows the population of each municipality in 2009 (inquiry report's estimate) and in 2021 (preliminary results from the 2021 census) (TIS, 2009).

We can see there are some population variations in the municipalities, with mostly rural areas losing population and urban areas maintaining. Although some variations are significant, such as in the municipality of Penacova and Soure (22.35 and 16.11%, respectively), we chose to maintain the number of trips without adjusting to these variations. This choice was based on the fact that these population variations are not that significant when considering the many estimates that have already been done until this point. Furthermore, as we will see in following chapters, the need for downsizing the total travel demand generated much more significant errors than these population variations did.

Table 4.1: Population variations of the municipalities of the Region of Coimbra

2009 Inquiry Estimates		2021 Census		% Variation	
Arganil	12798	Arganil	11 067	Arganil	-13.53%
Cantanhede	38930	Cantanhede	34 218	Cantanhede	-12.10%
Coimbra	140336	Coimbra	140 796	Coimbra	0.33%
Condeixa-a-Nova	17423	Condeixa-a-Nova	16 733	Condeixa-a-Nova	-3.96%
Figueira da Foz	63229	Figueira da Foz	58 982	Figueira da Foz	-6.72%
Góis	4446	Góis	3 806	Góis	-14.39%
Lousã	18787	Lousã	17 012	Lousã	-9.45%
Mealhada	22100	Mealhada	19 358	Mealhada	-12.41%
Mira	13269	Mira	12 126	Mira	-8.61%
Miranda do Corvo	13687	Miranda do Corvo	12 014	Miranda do Corvo	-12.22%
Montemor-o-Velho	24820	Montemor-o-Velho	24 587	Montemor-o-Velho	-0.94%
Mortágua	10217	Mortágua	8 960	Mortágua	-12.30%
Oliveira do Hospital	21714	Oliveira do Hospital	19 421	Oliveira do Hospital	-10.56%
Pampilhosa da Serra	4416	Pampilhosa da Serra	4 067	Pampilhosa da Serra	-7.90%
Penacova	16894	Penacova	13 119	Penacova	-22.35%
Penela	6287	Penela	5 443	Penela	-13.42%
Soure	20580	Soure	17 264	Soure	-16.11%
Tábua	12331	Tábua	11 163	Tábua	-9.47%
Vila Nova de Poiares	7491	Vila Nova de Poiares	6 813	Vila Nova de Poiares	-9.05%
TOTAL	469755	TOTAL	436949	TOTAL	-6.98%

4.2.2 Attribute table

Concerning the zone attribute table, data regarding the population of each zone was obtained from the report (although this data was not necessary for the simulation per se). Using the QGIS software to analyze the files provided regarding the inquiry's zoning, we obtained the centroid coordinates (in the WGS84 coordinate reference system) for each defined zone, as well as some data for the attribute table (zone ID, location coordinates: latitude and longitude, name designation and population size) which was then used as an input to the simulation model.

4.2.3 Origin/Destination table

Firstly, we extracted the final OD (Origin/Destination) table available in the mobility inquiry. In a first screening, we maintained information about the individual trip inquiry number, trip start time, origin zone, destination zone, type of inquiry and expansion coefficient (TIS, 2009).

Then, a process of trip selection was carried out. All trips that had either an origin or destination outside the region of Coimbra (area subjected to study) were deleted, in other words, trips with OD zones that did not belong to one of the 19 municipalities were removed. Trips within the same zone (short local trips), that is, trips with the same origin and destination zone ID, were also eliminated. These short trips within the same zone are mostly done by foot or bicycle and have a small duration of 10 to 15 minutes, thus amenable to be neglected.

From the previous selections, the number of trips decreased from 827601 to 467403. The expansion coefficient of each remaining individual trip inquiry was then rounded to the closest integer (0.137% increase in the number of trips due to rounding). Following, the OD table was expanded according to each trip's respective expansion coefficient, with the final OD table having a total of 468044 trips taking place within the region of Coimbra along the course of 24 hours. The final OD table was filtered once more and the only information that remained was an ID for each trip, an origin zone ID, a destination zone ID and a departure time (that was converted to seconds to match the model's time unit).

4.2.4 Downsizing total travel demand

Due to reasons that are explained in more detail in Section 3.3, there was a need to downsize the total travel demand. Starting from the final aggregated OD table referenced in Section 4.2.3, the table was downsized to multiple sizes. When a trip agent count would be less than 0.5, the agent count would always round up in order not to lose the type of trip represented (since rounding down would mean the agent count would be 0), for other number rounding, conventional rules would apply, with the decimal 0.5 or higher rounding up, and the lower than that rounding down. The total travel demand was downsized to approximately half its size, one fourth, one eighth, one tenth, and one twentieth, by respectively dividing it by 2, 4, 8, 10, 20, and then rounding trip agent count as mentioned.

This downsize induces some error due to the rounding. The 2 times smaller size sample maintains proportions between trips (since the smaller agent count is precisely 2), but from here on, any more downsize will have more and more disproportions between trips. It was discussed to remove some zones from the simulation, in order to maintain the original number of trips in the remaining zones while reducing the quantity of data, but we opted not to take this approach, since after removing a considerable amount of OD zones, the quantity of data would still be too large and downsizing would need to be done either way (it would not induce as much disproportion between trips, but it would still induce it). So rather than removing areas from the transport fleet service, we maintained all zones and thus maintain a variety of different trips. Table 4.2 shows examples of this transformation, for a sample 20 times smaller than the original travel demand.

Table 4.2: Examples of the total travel demand downsizing to a twentieth of the size

Original nº of trips	Divided by 20	Rounded
6	0.3	1
14	0.7	1
48	2.4	2
52	2.6	3
112	5.6	6

4.3 Mobility Statistics

4.3.1 Traveler average, highest and lowest Travel Time

The general travel time average of the 24458 travelers is 15.86 minutes (approximately 15 minutes and 52 seconds). The trip with the highest traveler travel time is 105 minutes and the lowest is 1 minute. We can verify in Figure 4.4, that shorter duration trips are the most common, with the 10 most frequent travel times being all under 15 minutes. The most frequent travel time is 6 minutes, with 1868 travelers making a trip with this duration. And the less frequent travel times are from longer duration trips, with 77, 102 and 103 minutes being the less common travel times (only one trip each). Note, that for analysis purposes, the travel times were rounded to their closest integer.

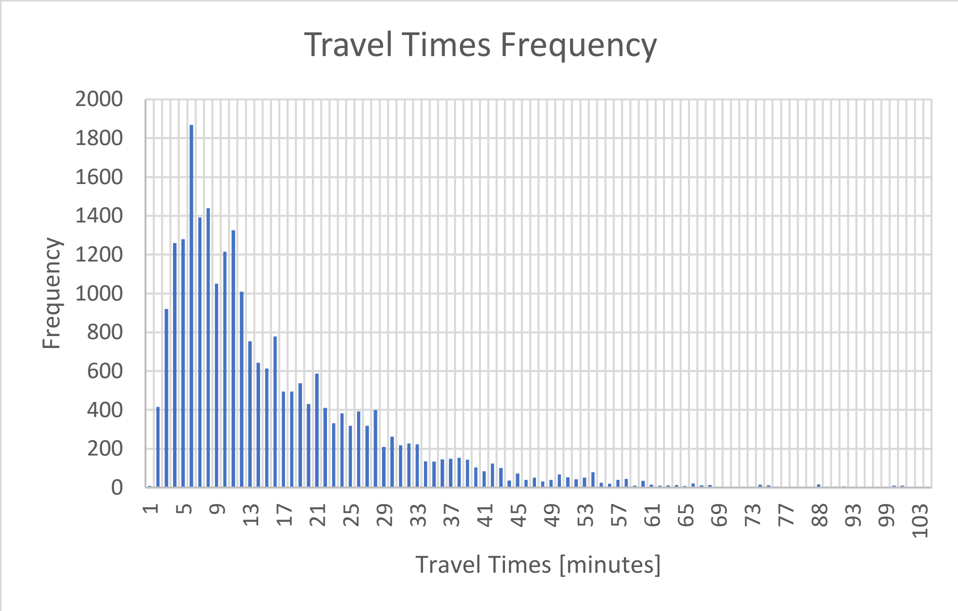

Figure 4.4: Travel times and their respective frequency

4.3.2 Most and less common Origins and Destinations

The most frequent trip origin is Zone 303 (with 1247 trips), which is in the Coimbra urban perimeter, more specifically, the "Baixa - Avenida Fernão de Magalhães" area, and the less frequent trip origin is Zone 133 (with 24 trips) in Soure (see Table 4.3). The most and less frequent trip destinations are very similar to the corresponding origins, with similar frequency also (see Table 4.4).

Table 4.3: Most and less frequent origin zones and their respective frequency

ORIGINS			
MOST FREQUENT	FREQUENCY	LESS FREQUENT	FREQUENCY
Zone 303	1247	Zone 133	24
Zone 301	962	Zone 49	29
Zone 65	904	Zone 38	36
Zone 315	875	Zone 206	36
Zone 302	869	Zone 304	36
Zone 312	726	Zone 55	38
Zone 320	570	Zone 348	38
Zone 307	565	Zone 210	39
Zone 6	541	Zone 9	40
Zone 326	486	Zone 37	40

Table 4.4: Most and less frequent destination zones and their respective frequency

DESTINATIONS			
MOST FREQUENT	FREQUENCY	LESS FREQUENT	FREQUENCY
Zone 303	1236	Zone 133	24
Zone 301	963	Zone 49	29
Zone 65	898	Zone 38	35
Zone 315	881	Zone 206	35
Zone 302	873	Zone 304	36
Zone 312	717	Zone 200	37
Zone 307	574	Zone 55	38
Zone 320	564	Zone 348	38
Zone 6	544	Zone 210	39
Zone 326	485	Zone 37	39

4.3.3 Trip Distribution

In Figure 4.5, we can see the trip distribution throughout the 24 hours of the day. As expected, we have two main peaks that correspond to the morning peak hour traffic and the evening peak traffic (these peaks correlate to business hours).

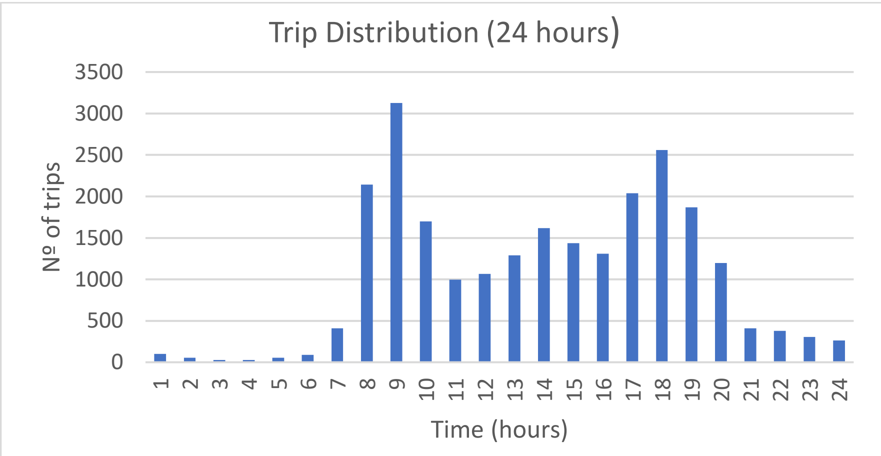

Figure 4.5: Trip distribution throughout the day (24 hours)

4.3.4 Case Study Scenarios

For the purpose of this work's analysis and based on what was stated in Section 3.3 regarding waiting time, five simulations were run with the following maximum waiting time values (in minutes): 5, 10, 15, 20 and 30. So, for each different Maximum Waiting Time scenario, one simulation was run. The Maximum Waiting Time was the only defined parameter that was different between the five scenarios.

5 RESULTS

5.1 PRESENTATION OF RESULTS

5.1.1 Traveler

Average Waiting Time

In Table 5.1 we have the traveler's average waiting time with and without null values, that is, the average of all traveler's waiting times and the waiting time average of all travelers that have a non-null waiting time (waiting time higher than zero). Since the system would generate a new car at the traveler's location in situations when there was no available vehicle that met the assignment criteria, the waiting time of that traveler would be 0 minutes.

Table 5.1: Traveler average Waiting Time with and without considering null values

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
AVERAGE WAITING TIME [minutes]	0.15	0.34	0.57	0.77	1.13
AVERAGE WAITING TIME (w/ null) [minutes]	2.64	4.43	6.23	7.61	9.94

Highest Waiting Time

The highest waiting times are presented in Table 5.2. As stated in Section 3.3.3, in a minority of cases, the traveler's waiting time will actually surpass the defined maximum, and here we see the highest of those values.

Table 5.2: Top 10 highest waiting times

	MAX WAITING TIME				
	5 min	10 min	15 min	20 min	30 min
10 HIGHEST WAITING TIMES [minutes]	27.10	26.54	37.34	44.02	68.51
	19.04	25.85	37.23	42.35	51.62
	15.96	25.81	36.37	39.18	50.09
	11.76	25.35	30.79	39.17	49.07
	11.61	21.80	30.17	38.78	49.05
	11.11	21.44	30.17	38.72	47.61
	10.98	20.75	30.17	38.08	47.49
	10.96	20.25	29.99	37.90	47.46
	10.63	19.98	28.73	37.36	46.07
	10.53	19.94	28.69	37.34	45.67

Maximum Waiting Time success rate

Following-up what was stated above, since there are traveler waiting times that surpass the defined maximum, we can calculate the success rate of a traveler being served within time (see Table 5.3). We can verify that these rates are similar for the different Maximum Waiting Times, nonetheless, there is a slight failure rate decrease trend as we increase the Maximum Waiting Time, i.e., as Maximum Waiting Time increases, so does the success rate of the traveler being served in time.

Table 5.3: Number and percentage of travelers that were picked up after the defined Maximum Waiting Time

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
NUMBER OF TRAVELER WT > MAX WT	175	160	189	148	126
% OF WT > MAX WT	0.72%	0.65%	0.77%	0.61%	0.52%

5.1.2 Car

Trips

The average number of trips that a vehicle completes during the simulation is presented in Table 5.4. In Table 5.5, we can see that the highest number of trips done by a vehicle is somewhat similar for every simulation.

Table 5.4: Average number of trips done per vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
AVERAGE NUMBER OF TRIPS PER VEHICLE	1.40	1.43	1.46	1.48	1.50

Table 5.5: Top 10 highest number of trips done by a vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
TOP 10 Nº TRIPS PER VEHICLE	41	41	39	43	37
	39	38	38	40	37
	38	38	37	40	37
	37	37	37	39	36
	37	36	37	39	36
	36	35	36	39	36
	36	35	35	37	35
	35	35	35	36	35
	34	34	35	36	35
	32	34	35	36	35

Distance Driven

We can verify that the average Distance Driven, both per vehicle and per trip, and the total Distance Driven, increases as the Maximum Waiting Time increases (Table 5.6). The highest distance driven by a vehicle can vary a little but is somewhat similar between the different simulations (see Table 5.7). The Distance Driven registered, as explained in Section 3.3.4, is a straight-line distance. So, the distances and averages showed in the following tables are straight-line distance. Nonetheless, to give a rough idea of the real distance, we a calculated an increase factor, by choosing 50 random trips (about half from urban areas, other half from rural areas) and calculating the ratio between the simulated (straight-line) distance and the real road distance. The average of those 50 ratios, is a factor of approximately 1.5.

Table 5.6: Average distance driven per vehicle and per vehicle trip, and total distance driven

	MAX WAITING TIME				
	5 MIN	**10 MIN**	**15 MIN**	**20 MIN**	**30 MIN**
AVERAGE DISTANCE DRIVEN PER VEHICLE [Kilometers]	12.721	13.140	13.490	13.756	14.167
AVERAGE DISTANCE PER VEHICLE TRIP [Kilometers]	9.113	9.170	9.238	9.300	9.414
TOTAL DISTANCE DRIVEN [Kilometers]	222877	224280	225939	227453	230245

Table 5.7: Top 10 highest distance driven by a vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
TOP 10 VEHICLES DISTANCE DRIVEN (Kilometers)	438.350	454.943	520.092	523.018	488.373
	417.924	425.082	446.119	484.579	459.897
	408.893	412.664	424.895	473.650	451.194
	391.144	409.081	423.744	468.585	442.141
	373.167	401.868	410.099	462.692	441.934
	372.590	401.666	409.629	432.493	426.150
	368.973	400.425	402.547	424.800	425.277
	367.661	390.045	402.413	423.360	416.130
	365.763	384.665	401.100	419.127	413.221
	363.634	380.699	396.731	417.888	405.385

Battery Usage

Just as Distance Driven, the Battery Usage average per vehicle and vehicle trip, and the total energy used (Table 5.8), increases with the Maximum Waiting Time (this is normal, since Battery Usage depends on speed and distance). The highest values are also similar between simulations (Table 5.9).

Table 5.8: Average battery usage per vehicle and per vehicle trip, and total energy expenditure

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
AVERAGE BATTERY USED PER VEHICLE [Wh]	1320	1363	1398	1425	1468
AVERAGE BATTERY USED PER VEHICLE TRIP [Wh]	946	951	957	963	975
TOTAL ENERGY EXPENDITURE [kWh]	23132	23261	23418	23564	23852

Table 5.9: Top 10 highest battery usage by a vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
TOP 10 VEHICLES BATTERY USED (kWh)	54.396	50.594	55.011	58.476	55.485
	45.889	49.060	50.590	56.034	51.056
	44.981	47.753	46.233	55.004	48.474
	44.536	47.394	45.860	52.912	47.514
	43.577	47.330	45.640	52.866	47.292
	43.525	45.393	45.446	51.053	44.110
	42.188	44.421	45.384	48.849	44.066
	39.389	42.589	43.834	48.203	43.572
	38.815	41.628	42.692	47.833	43.422
	38.700	41.513	42.246	46.234	42.633

Charging

The average number of charges per vehicle is presented in Table 5.10, and the highest values of charges per vehicle are presented in Table 5.11.

Table 5.10: Average number of charges per vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
AVERAGE Nº OF CHARGES PER VEHICLE	1.006	1.006	1.008	1.007	1.009

Table 5.11: Top 10 highest number of charges done by a vehicle

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
TOP 10 Nº OF CHARGES PER VEHICLE	4	4	4	4	4
	4	4	4	4	4
	4	4	4	4	4
	4	4	4	4	4
	4	4	4	4	4
	4	3	4	3	3
	4	3	4	3	3
	4	3	3	3	3
	3	3	3	3	3
	3	3	3	3	3

Finish Zone

In Table 5.12 and Table 5.13 we can verify the most common finishing zones for the vehicles and their respective frequency. These zones correspond exactly to the most common destinations (see Table 4.4) and are the same for every simulation, although the order of frequency can change.

Table 5.12: Top 10 most common vehicle end zones and their respective frequency (a)

	MAX WAITING TIME					
	5 MIN		10 MIN		15 MIN	
	ZONE ID	FREQUENCY	ZONE ID	FREQUENCY	ZONE ID	FREQUENCY
TOP 10 FINISH ZONES ID	303	1036	303	1004	303	994
	301	753	301	738	301	737
	65	734	65	713	65	702
	315	717	315	708	315	702
	302	711	302	701	302	687
	312	565	312	551	312	549
	307	458	307	453	307	450
	320	435	6	431	6	421
	6	434	320	422	320	417
	326	365	326	356	326	343

Table 5.13: Top 10 most common vehicle end zones and their respective frequency (b)

	MAX WAITING TIME			
	20 MIN		30 MIN	
	ZONE ID	FREQUENCY	ZONE ID	FREQUENCY
TOP 10 FINISH ZONES ID	303	987	303	974
	301	728	301	717
	315	695	315	695
	65	694	65	680
	302	682	302	675
	312	543	312	528
	307	446	307	444
	6	418	320	413
	320	415	6	406
	326	338	326	337

5.1.3 Zone Charges

Total Charges

The number of total charges per zone is how many times a vehicle charged in that zone throughout the day. The average number of charges per zone and the total number of charges decreases with increasing Maximum Waiting Time (see Table 5.14). Although the average in the simulations is between 120 and 130 charges per zone, the number of charges per zone varies greatly among different zones, from above 1000 charges to only 14 charges in some zones (see Table 5.15, Table 5.16, Table 5.17 and Table 5.18).

Table 5.14: Average and total number of charges per zone

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
AVERAGE NUMBER OF CHARGES PER ZONE	129.3	126.0	123.8	122.1	120.2
TOTAL NUMBER OF CHARGES	17714	17258	16959	16732	16474

Table 5.15: Top 10 zones with most charges done and their respective charges (a)

	MAX WAITING TIME					
	5 MIN		10 MIN		15 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 MOST CHARGES ZONES	303	1036	303	1004	303	994
	301	753	301	738	301	737
	65	734	65	713	65	702
	315	717	315	708	315	702
	302	711	302	701	302	687
	312	565	312	551	312	549
	307	458	307	453	307	450
	320	435	6	431	6	421
	6	434	320	422	320	417
	326	365	326	356	326	343

Table 5.16: Top 10 zones with most charges done and their respective charges (b)

	MAX WAITING TIME			
	20 MIN		30 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 MOST CHARGES ZONES	303	987	303	974
	301	728	301	717
	315	695	315	695
	65	694	65	680
	302	682	302	675
	312	543	312	528
	307	446	307	444
	6	418	320	413
	320	415	6	406
	326	338	326	337

Table 5.17: Top 10 zones with less charges done and their respective charges (a)

	MAX WAITING TIME					
	5 MIN		10 MIN		15 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 LESS CHARGES ZONES	49	17	49	16	49	14
	50	20	50	18	50	17
	133	20	133	19	133	19
	37	21	38	20	55	19
	38	21	37	21	38	20
	53	22	53	22	37	20
	55	24	55	23	53	20
	9	26	9	23	210	23
	210	28	52	25	52	24
	304	28	112	27	9	25

Table 5.18: Top 10 zones with less charges done and their respective charges (b)

	MAX WAITING TIME			
	20 MIN		30 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 LESS CHARGES ZONES	49	14	49	15
	37	17	53	17
	38	18	38	18
	50	19	37	19
	133	20	50	19
	55	20	55	19
	53	22	133	20
	9	23	9	21
	210	24	52	24
	52	24	304	24

Simultaneous Charges

Regarding charging stations, this parameter is one of the most important, since it represents the maximum number of vehicles charging at any given time, which can then be used to estimate the number of charging ports needed. In Table A.2 in the Appendix, we can see these values for every zone. In Table 5.19 and Table 5.20 we can see the zones with highest number of simultaneous charges, and in Table 5.21 and Table 5.22 we can see the zones with lower number.

Table 5.19: Top 10 zones with most simultaneous charges done and their respective charges (a)

	MAX WAITING TIME					
	5 MIN		10 MIN		15 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 MOST SIM CHARGES	303	94	303	91	303	91
	65	84	65	84	65	81
	302	65	302	63	315	65
	315	63	315	63	302	62
	312	56	312	53	312	53
	301	51	301	51	301	51
	307	43	307	43	6	42
	321	40	321	39	307	42
	320	39	320	38	321	39
	328	37	204	36	320	38

Table 5.20: Top 10 zones with most simultaneous charges done and their respective charges (b)

	MAX WAITING TIME			
	20 MIN		30 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 MOST SIM CHARGES	303	90	303	96
	65	81	65	84
	315	62	302	61
	302	59	315	61
	312	53	312	54
	301	50	301	51
	307	43	307	43
	321	39	6	41
	6	39	321	39
	320	36	320	36

Table 5.21: Top 10 zones with less simultaneous charges done and their respective charges (a)

	MAX WAITING TIME					
	5 MIN		10 MIN		15 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 LESS SIM CHARGES	49	3	49	3	49	3
	9	4	9	4	53	3
	37	4	37	4	37	4
	38	4	38	4	38	4
	53	4	53	4	59	4
	59	4	59	4	112	4
	133	4	112	4	133	4
	52	5	133	4	9	5
	112	5	29	5	29	5
	213	5	52	5	52	5

Table 5.22: Top 10 zones with most simultaneous charges done and their respective charges (b)

	MAX WAITING TIME			
	20 MIN		30 MIN	
	ZONE ID	CHARGES	ZONE ID	CHARGES
TOP 10 LESS SIM CHARGES	53	3	29	3
	49	3	37	3
	37	3	49	3
	133	4	53	3
	112	4	9	4
	59	4	38	4
	38	4	55	4
	358	5	59	4
	337	5	112	4
	213	5	133	4

Following, we have a chart with 5 curves (one for each simulation) with total number of charging vehicles at any given minute throughout the day (Figure 5.1). As it can be seen, these curves are very similar, with only some small variations.

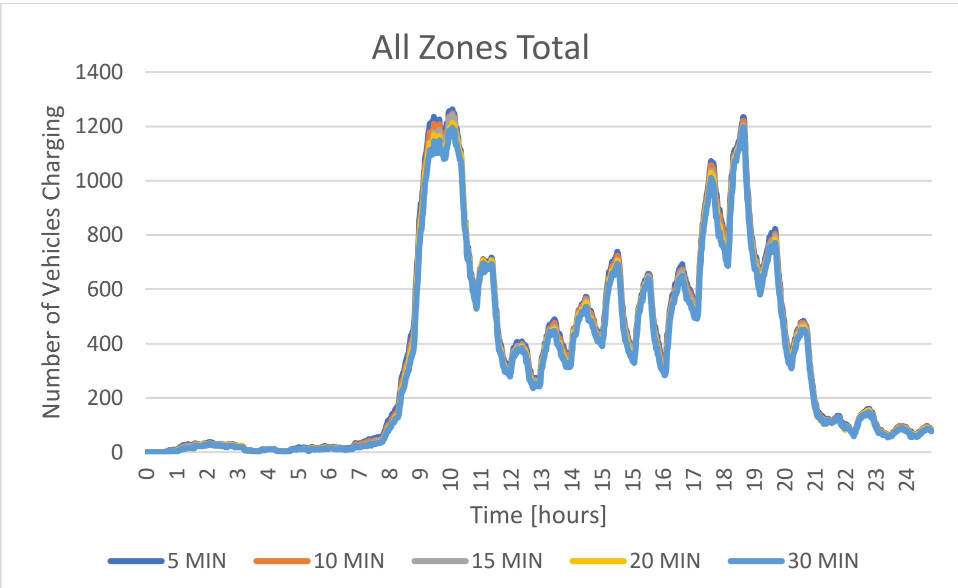

Figure 5.1: Total number of charging vehicles at any given minute throughout the day (defined maximum Waiting Time of 5, 10, 15, 20 and 30 minutes)

In Figure 5.2 and Figure 5.3, we can see these same curves for three urban area zones (Coimbra, Figueira da Foz and Cantanhede) and three rural area zones (Soure, Pampilhosa da Serra and Penacova), respectively. While the urban area zones approximately follow the curve in Figure 5.1, the rural area zones diverge more from this pattern.

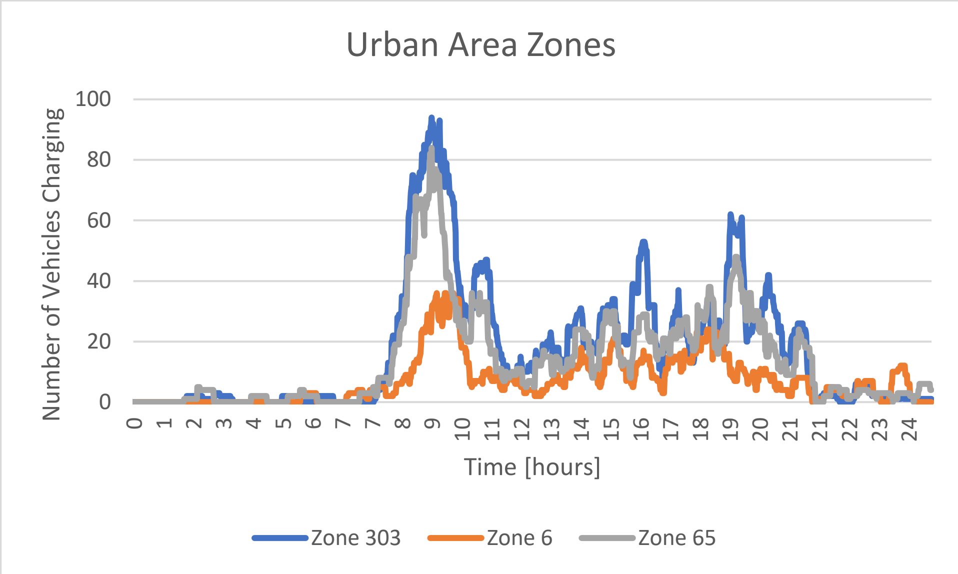

Figure 5.2: Number of charging vehicles at any given minute throughout the day (defined maximum Waiting Time of 5 minutes) in urban area zones

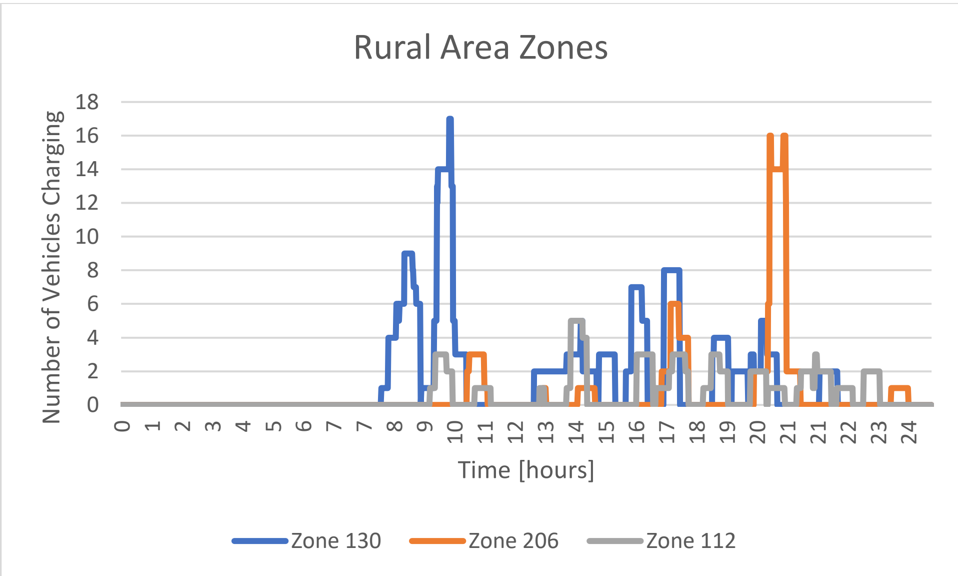

Figure 5.3: Number of charging vehicles at any given minute throughout the day (defined maximum Waiting Time of 5 minutes) in rural area zones

5.1.4 Vehicle Fleet Size

Finally, in the following charts, we have the analysis that gives us the variation of vehicle fleet size depending on Maximum Waiting Time. From the data in Table 5.23, we can create a scatter chart and trace a variation line and equation. In Figure 5.4, we have the trendline (which is a logarithmic curve) and respective equation for the variation rate of vehicle fleet size depending on Maximum Waiting Time. In Figure 5.5 and Figure 5.6, we see this curve but represented in relation to the average Waiting Time (with and without null values, respectively).

Table 5.23: Number of vehicles generated in each simulation

	MAX WAITING TIME				
	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
NUMBER OF VEHICLES	17521	17068	16749	16535	16252

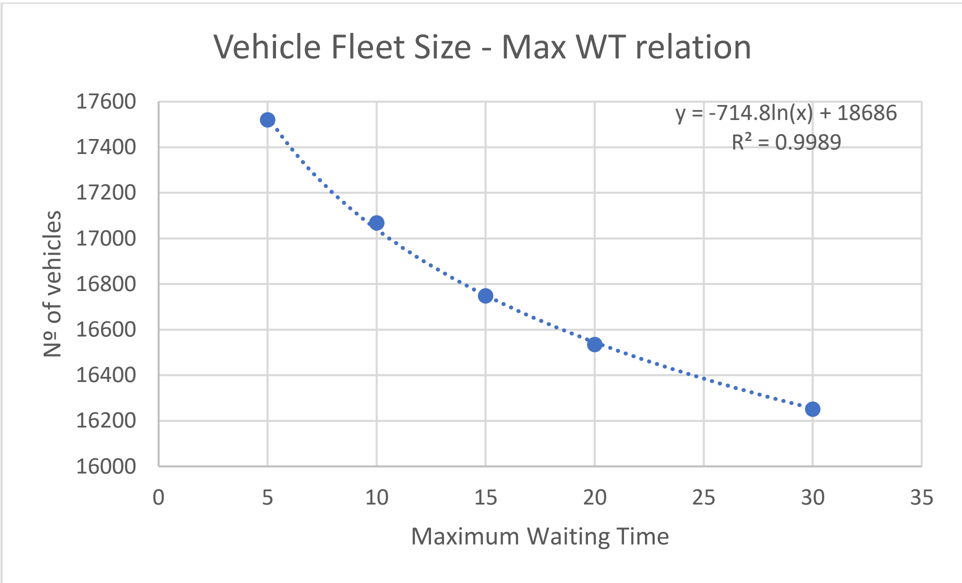

Figure 5.4: Vehicle fleet size variation with increasing maximum Waiting Time

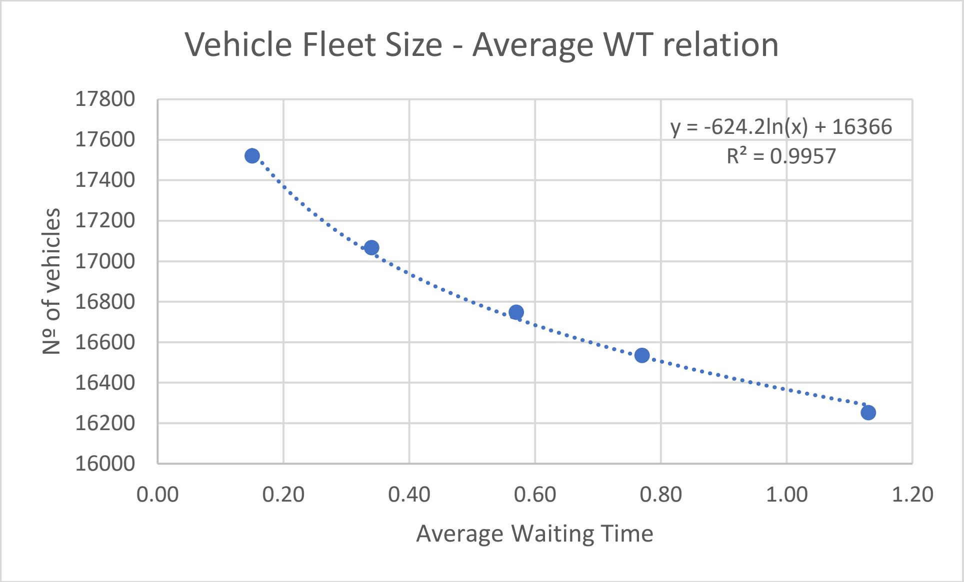

Figure 5.5: Vehicle fleet size variation compared to the average Waiting Time of the simulations

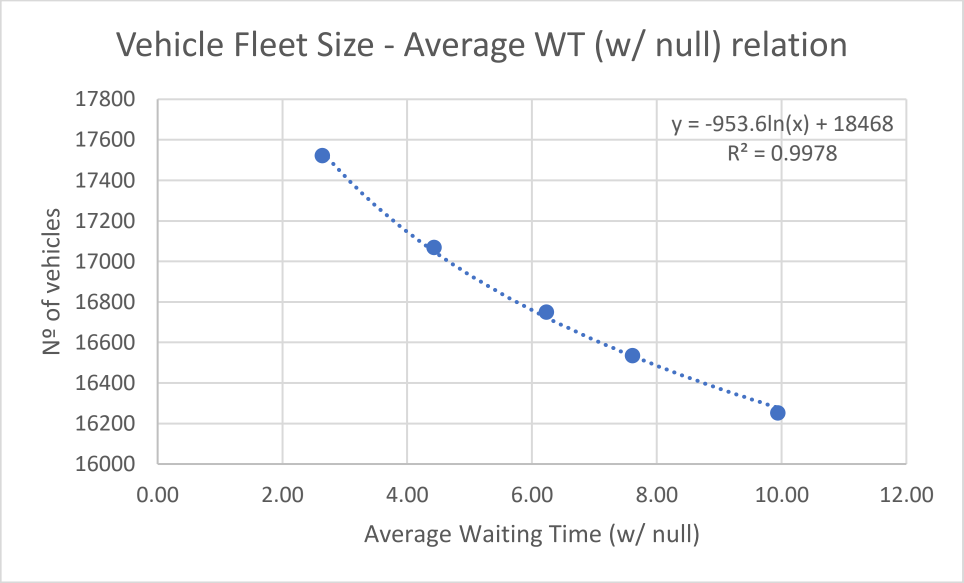

Figure 5.6: Vehicle fleet size variation compared to the average Waiting Time (without null values) of the simulations

5.2 DISCUSSION OF RESULTS

It was expected that the number of vehicles needed for the transport service fleet would decrease with the increase of maximum waiting time, and the results showed this. Nonetheless, we expected a higher decrease rate. Comparing to the lowest Maximum Waiting Time tested (5 minutes), increasing this time to 10 minutes lowered the number of vehicles needed by 2.59%, to 15 minutes by 4.41%, to 20 minutes by 5.63% and to 30 minutes by 7.24%. So, we can see that by increasing the time six-fold, we only decreased the number of vehicles needed by 7.24%. These results are expectedly due to multiple factors. One reason may be the fact that the main focus of this study was interurban trips, thus, many shorter trips with a small Maximum Waiting Time radius, would meet vehicle assignment criteria, so by increasing Maximum Waiting Time, there would be considerably more travelers served with less cars. Another reason may be the fact that we did not fully employ the ridesharing feature (only time-sharing vehicles, not space-sharing). With space-sharing vehicles, multiple travelers could travel in one single car, further reducing the vehicle fleet size needs. Downsizing the total travel demand also may be one of the main factors, since due to rounding, trips representation became highly disproportional. A trip that initially represented 29 traveler trips, after downsizing represents only 1 traveler trip, while a trip that initially represents 1 traveler trip, after downsizing still represents 1 traveler trip.

Besides the problems described above, some other model limitations include vehicle relocation, charging, vehicle and travel request generation, warm-up period and simulated time. Regarding vehicle relocation, despite not being considered in this model, its effect would not have been significant, since there is a scheduled systematic trend in the flow of traffic, with an approximately equal number of travelers going in one direction at the beginning of the day and returning in the opposite direction at the end of the day. Nonetheless, it should be noted that depending on each case, relocation can be beneficial in multiple aspects, and if, for example, there were fewer charging stations and they would only be located in certain areas, in this case, relocation would have a more significant role. Concerning charging, as stated in Section 3.3.3, we assumed that the vehicle's battery would start with 50% charge. Since many vehicles in this simulation only did one trip, they would consequently park and after 30 minutes, they would charge (because every generated new vehicle's battery was below 90% charge). Many of these trips were short, so the amount of battery used was small, which means, if the vehicle's battery would've have been generated fully charged, the number of charges done would've been considerably lower. Regarding vehicle and travel request generation, the vehicles were generated at the exact location of the travel request, thus, the waiting time was zero (unrealistic waiting time). Ideally, the traveler request should've been generated at a random location within a populated area of the zone and the car should've been generated randomly or at specific chosen location within the traveler's zone. Still on the subject of vehicle generation, this study also didn't include a "warm-up", where there would be a first simulation to generate the cars and estimate the fleet size, and then a second simulation would be run with the vehicles already generated at their respective location. Unfortunately, due to the long simulation running times, this was not possible to do. Note that, for the vehicle fleet size estimate, there is no need for a warm-up, but for obtaining other parameters, such as, more realist waiting times, this process should be done. Finally, the simulation was only run for one day's trips. Preferably, the simulation would include multiple days (for example, an entire week), with possibly some small random variations, to create continuity between the simulated days and give results more approximate to reality.

Despite the multiple limitations, the significance of the results of this study is mainly affected by the downsizing of the total travel demand. For real world applications, the simulations should have been run with the original total travel demand as input. Notwithstanding, the model built was prepared to run full size simulations during multiple days, but due to the software's limitations regarding running time, this was by far unfeasible.

6 CONCLUSION

This work provided a global overview regarding the subject of autonomous vehicles and agent-based model simulation. We first introduced multiple concepts, such as, autonomous vehicles, ridesharing, electric vehicles, shared autonomous vehicles, simulation and agent-based models. We addressed many of the potential benefits that come with the implementation of autonomous vehicles and some major issues to consider. Potential benefits include increase in road safety, less traffic and emissions, changes in travel behavior and accessability, revolutinizing freight transportation and a significant positive economic impact. Major issues involve high vehicle costs, lagging legislation and regulations, liability and ethics approaches, security threats, privacy issues and lacking research. Concerning agent-based models, we revised two recent systematic reviews regarding the subejct and complemented by reviewing a study example. The overview of the existing literarture included date and geographic distribution, data collection, simulation key variables, model execution, scenario variations, outputs and analysis of results. In the study example, we reviewed model specifications, operations, application and implementation. A methodology was developed to design an SAEV system and its components using simulation. The general model procedure, model development and post-simulation analysis were described. The methodology includes an agent-based simulation model with zones, travelers and vehicles as agents, allowing for them to interact based on input data and defined parameters. The ABM model was implemented using a software tool available in the market (Anylogic). The Region of Coimbra (NUTS III) served as a testbed for the methodology. A background of this region was presented, along with mobility statistics and the data processing steps that were done. Results showed that by increasing maximum waiting time, there is a logarithmic decrease of the vehicle fleet size needed. In addition to these results, statistics regarding travelers, vehicles and charging zones were showed. Finally, there was a discussion concerning the results, in which the interpreation of results and their sigfinicance and validity was addressed.

To summarize, we can divide the case study steps in three stages. The first stage consisted of analyzing data and diagnosing the current mobility situation of the region using said data. The second stage consisted of designing the model and building it in the simulation software, where we introduce an autonomous vehicle fleet providing transfer services, with a time-sharing only fleet. The third stage focused on the introduction of electric functioning vehicles and charging ports. Besides the case study development, an introduction to certain concepts regarding the subject at hand, and a review of the literature related to autonomous vehicles and existing simulation models was also done. Finally, after all simulations were ran, their results were analyzed, compared and discussed.

In future work, fully ridesharing vehicles with two or more seats should be considered. Multiple battery and charging capacities should be tested, along with different charging scenarios (for example, considering electricity charging cost, which is cheaper at night). For a real-world scenario preparation, optimization work regarding the charging stations' location should be done also. OD zone divisions should be better adjusted according to type and quantity of the travel requests and other forms of public transportation functioning in parallel could also be considered to be available for the traveler (with possibly different costs taken into consideration). Other factors such as vehicle relocation and traveler location generation can also lead to better results.

To conclude this work, we should note that autonomous technology is already presently working and always improving. Just as it was stated in the introduction of this thesis, the era of autonomous driving is coming, and we should prepare for it. This work and the project in which it is inserted, aims to contribute to this purpose.

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APPENDIX A

Table A.1: Zones' Attribute Table, with ID, coordinates, name and population

ZONA	Longitude	Latitude	Designação	População
1	-8.740332	40.415207	Mira	8022
2	-8.628689	40.398116	Cantanhede	3690
3	-8.679095	40.391049	Cantanhede	2632
6	-8.60488	40.353889	Cantanhede	8450
8	-8.527283	40.268654	Cantanhede	2649
9	-8.549431	40.301177	Cantanhede	1261
16	-8.479111	40.397729	Mealhada	2359
18	-8.442709	40.380881	Mealhada	4306
19	-8.467936	40.346125	Mealhada	3513
20	-8.404707	40.364338	Mealhada	2215
21	-8.42949	40.33872	Mealhada	4492
22	-8.349015	40.29154	Penacova	2869
23	-8.327612	40.250669	Penacova	4263
24	-8.273208	40.280919	Penacova	3620
25	-8.275755	40.213098	Vila Nova de Poiares	5655
27	-8.208394	40.223273	Vila Nova de Poiares	1836
29	-8.2674	40.164537	Lousã	1757
30	-8.191125	40.164539	Lousã	2042
32	-8.24669	40.102167	Lousã	12397
33	-8.209645	40.126087	Lousã	2591
34	-8.324849	40.157026	Miranda do Corvo	4074
35	-8.328149	40.098031	Miranda do Corvo	7478
37	-8.376595	40.08789	Miranda do Corvo	979
38	-8.300948	40.054129	Miranda do Corvo	1156
39	-8.524728	40.142682	Condeixa-a-Nova	3894
42	-8.550677	40.09827	Condeixa-a-Nova	3273
43	-8.499543	40.117144	Condeixa-a-Nova	4521
44	-8.475493	40.09815	Condeixa-a-Nova	3769
48	-8.612806	40.0531	Soure	8313
49	-8.595723	40.146049	Soure	1643
50	-8.625389	40.118123	Soure	1295
51	-8.630926	40.159767	Soure	1641
52	-8.650048	40.150291	Soure	1539
53	-8.569911	40.169352	Montemor-o-Velho	2183
54	-8.595516	40.233804	Montemor-o-Velho	2216
55	-8.629348	40.221093	Montemor-o-Velho	1672
56	-8.634074	40.205953	Montemor-o-Velho	3013
57	-8.6091	40.172867	Montemor-o-Velho	1464

58	-8.672715	40.188947	Montemor-o-Velho	2779
59	-8.70959	40.135254	Montemor-o-Velho	2448
63	-8.804989	40.137765	Figueira da Foz	3225
64	-8.8389	40.170334	Figueira da Foz	7800
65	-8.854918	40.152024	Figueira da Foz	10957
66	-8.853562	40.129596	Figueira da Foz	2732
67	-8.880607	40.180998	Figueira da Foz	8131
100	-8.790587	40.446197	Mira	3077
101	-8.728616	40.465223	Mira	2170
102	-8.601844	40.443669	Cantanhede	3428
103	-8.530723	40.383364	Cantanhede	3546
104	-8.516612	40.340842	Cantanhede	2743
105	-8.659142	40.319465	Cantanhede	6407
106	-8.782807	40.34177	Cantanhede	4124
110	-8.379019	40.38148	Mealhada	2929
111	-8.484381	40.30259	Mealhada	2286
112	-8.318394	40.331616	Penacova	1809
113	-8.189986	40.301533	Penacova	4333
114	-8.462623	40.071658	Condeixa-a-Nova	1966
123	-8.8409	40.039687	Figueira da Foz	3274
124	-8.845198	40.085293	Figueira da Foz	4213
125	-8.780644	40.060248	Figueira da Foz	3391
126	-8.780794	40.097009	Figueira da Foz	1982
127	-8.788647	40.192223	Figueira da Foz	4110
128	-8.778227	40.239	Figueira da Foz	9304
129	-8.844987	40.221392	Figueira da Foz	4110
130	-8.704299	40.078089	Soure	4213
131	-8.675576	40.277235	Montemor-o-Velho	5802
132	-8.704602	40.238568	Montemor-o-Velho	3243
133	-8.516146	40.008614	Soure	1936
200	-8.253141	40.41952	Mortágua	10217
202	-8.01518	40.334164	Tábua	12331
203	-7.863711	40.368464	Oliveira do Hospital	21714
204	-8.079163	40.227601	Arganil	8166
205	-7.908224	40.230224	Arganil	4632
206	-7.916355	40.084317	Pampilhosa da Serra	4416
210	-8.369832	40.010123	Penela	6287
213	-8.089421	40.10254	Góis	4446
301	-8.423912	40.206383	Alta / Universidade Pólo I	1694
302	-8.420175	40.209284	Av Sá da Bandeira / Praça da República	1303
303	-8.433597	40.212488	Baixa / Avde Fernão de Magalhães	2163
304	-8.421227	40.222967	Coselhas	744

305	-8.42426	40.199101	Parque	244
306	-8.429294	40.191971	Quinta das Lágrimas / Quinta da Várzea	1663
307	-8.438773	40.207853	Rossio de Santa Clara / Guarda Inglesa	1592
308	-8.421422	40.213499	Montes Claros	3571
309	-8.431252	40.217115	Conchada	1536
310	-8.420119	40.217567	Rua Padre Manuel da Nóbrega	1326
311	-8.413192	40.214314	Cruz de Celas	1183
312	-8.409453	40.220571	Bairro de Celas / Hospital	1186
313	-8.407176	40.213396	Olivais / Cumeada	2486
314	-8.41331	40.208115	Av Dias da Silva / Loios / Cidral	1838
315	-8.406973	40.204606	Solum	4018
316	-8.417386	40.197054	Arregaça	1459
317	-8.416201	40.201473	Rua do Brasil	2275
318	-8.408955	40.198864	Bairro Norton de Matos	5016
319	-8.401124	40.197631	Casa Branca	1125
320	-8.410233	40.194736	Vale das Flores	3573
321	-8.417796	40.186593	Quinta da Boavista / Universidade Pólo II	1034
322	-8.406457	40.186153	Alto de São João / Quinta da Portela	1323
323	-8.444461	40.202884	Almas de Freire / Vale Gemil	3126
324	-8.446085	40.186897	Alto dos Barreiros / Cruz dos Morouços	2460
325	-8.452463	40.196815	Mesura / Póvoa	2017
326	-8.463025	40.195601	Covões / Espírito Santo das Touregas	3363
327	-8.475301	40.197838	Fala	4171
328	-8.461714	40.213938	São Martinho do Bispo / Bencanta	2592
329	-8.478468	40.208185	Casais	2492
330	-8.44351	40.226841	Loreto	3549
331	-8.432564	40.226265	Monte Formoso / Ingote	3903
332	-8.426315	40.238023	Bairro de São MIguel / Bairro da Liberdade	1653
333	-8.442946	40.2425	Pedrulha	1938
334	-8.433982	40.257536	Adémia / Bairro de Santa Apolónia	4525
335	-8.420622	40.248631	Eiras	1621
336	-8.411845	40.232453	Lordemão	1856
337	-8.393651	40.211888	Tovim de Baixo	980
338	-8.399685	40.216884	São Sebastião / Av Elísio de Moura	3182
339	-8.401877	40.211925	Quinta da Maia	1797
340	-8.395035	40.203611	Chão do Bispo	2376
341	-8.394676	40.191686	Areeiro	1430
342	-8.385452	40.212374	Tovim de CIma	1269
343	-8.365241	40.183222	Ceira	5056
344	-8.419952	40.158381	Castelo Viegas - freguesia e Assafarge	2091
345	-8.456714	40.169343	Antanhol / Palheira e Carvalhais	3170
347	-8.504439	40.19628	Taveiro	3201

348	-8.487464	40.180724	Ribeira de Frades / Valongo	1046
349	-8.476805	40.238692	Antuzede	2145
350	-8.537999	40.223396	São Silvestre - SM Árvore	3740
351	-8.570021	40.256278	Lamarosa	2158
352	-8.514385	40.241397	São João do Campo - freguesia	2168
353	-8.465833	40.272732	Vil de Matos - freguesia e Trouxemil / Torre de	3477
355	-8.426	40.296445	Souselas - freguesia	2953
356	-8.396481	40.320057	Botão - freguesia	1580
357	-8.396482	40.269563	Brasfemes - freguesia	1742
358	-8.38183	40.24563	São Paulo de Frades / Rocha Nova	1694
359	-8.354748	40.215646	Casal do Lobo / Dianteiro	1182
360	-8.375803	40.205042	Torres do Mondego	1120
361	-8.391129	40.132129	Almalaguês - freguesia	3229
362	-8.464169	40.135317	Cernache - freguesia	3674
364	-8.536687	40.182761	Ameal / Arzila - freguesia	2258

Table A.2: Number of total daily charges per zone

Zone ID	5 MIN	10 MIN	15 MIN	20 MIN	30 MIN
1	93	81	72	76	71
2	71	67	67	65	57
3	43	37	33	30	33
6	347	332	336	327	329
8	65	57	53	55	53
9	26	23	25	23	21
16	45	45	48	45	45
18	203	186	175	173	173
19	69	64	65	62	62
20	47	46	44	42	41
21	110	100	98	89	91
22	31	28	29	24	26
23	50	49	48	48	45
24	109	108	90	93	88
25	81	85	88	81	78
27	38	39	40	37	37
29	31	28	27	28	25
30	93	89	86	87	85
32	256	248	235	232	231
33	109	113	110	107	108
34	85	83	81	79	79
35	180	176	174	174	161
37	21	21	20	17	19

38	21	20	20	18	18
39	81	80	74	73	73
42	43	39	40	39	36
43	144	142	140	130	122
44	54	51	43	46	43
48	142	139	136	142	136
49	17	16	14	14	15
50	20	18	17	19	19
51	44	46	43	42	40
52	29	25	24	24	24
53	22	22	20	22	17
54	36	35	34	32	29
55	24	23	19	20	19
56	61	60	60	57	57
57	33	31	31	29	28
58	214	207	195	196	195
59	31	31	29	29	28
63	82	80	79	72	74
64	274	265	264	263	257
65	682	666	654	652	640
66	136	134	131	127	122
67	238	227	226	225	218
100	62	62	59	56	53
101	54	52	55	53	52
102	52	53	53	51	49
103	84	83	77	74	74
104	71	70	70	68	67
105	130	128	127	126	120
106	99	98	98	98	93
110	68	70	68	67	66
111	64	65	63	61	60
112	30	27	32	30	29
113	107	105	105	102	100
114	35	36	36	35	36
123	74	74	68	66	66
124	145	144	137	135	130
125	67	62	62	62	61
126	33	34	34	32	31
127	94	92	91	89	90
128	187	185	180	177	172
129	88	86	84	85	84
130	72	72	72	65	65

131	96	93	95	94	91
132	55	54	55	55	56
133	20	19	19	20	20
200	30	29	27	26	27
202	75	75	74	73	70
203	76	75	73	69	68
204	132	130	129	127	126
205	51	51	50	50	49
206	30	29	28	27	28
210	28	28	23	24	25
213	32	31	30	28	25
301	621	611	603	603	592
302	563	544	533	522	517
303	849	824	816	807	793
304	28	28	25	24	24
305	63	66	64	63	68
306	111	106	103	104	103
307	420	412	406	404	402
308	229	222	223	219	220
309	73	72	72	73	75
310	121	123	124	122	123
311	248	240	235	234	228
312	544	529	527	520	511
313	154	148	150	149	147
314	340	336	329	324	323
315	644	639	637	629	622
316	76	74	74	73	71
317	205	196	195	195	192
318	198	194	193	190	192
319	87	85	84	83	83
320	425	415	411	409	404
321	347	338	336	329	319
322	196	197	196	194	192
323	127	124	121	121	120
324	83	83	84	84	81
325	75	72	71	70	70
326	370	360	347	345	342
327	131	125	123	122	121
328	322	309	304	302	295
329	99	96	95	94	93
330	185	179	179	178	172
331	130	127	126	126	124

332	93	92	92	90	89
333	137	133	129	129	127
334	194	192	191	189	185
335	95	91	89	87	86
336	77	74	72	72	73
337	29	29	29	30	29
338	133	129	128	127	128
339	83	82	82	82	82
340	112	111	109	110	109
341	77	77	77	76	75
342	51	52	51	50	49
343	181	176	174	175	171
344	59	53	54	54	54
345	102	102	97	96	96
347	212	204	201	198	192
348	29	29	29	29	29
349	76	73	71	71	72
350	122	119	120	119	118
351	61	59	56	57	57
352	61	61	58	61	58
353	142	141	138	135	135
355	132	127	122	120	121
356	39	39	40	39	37
357	40	38	38	37	37
358	35	35	30	25	25
359	41	37	38	30	31
360	88	81	80	80	79
361	89	89	88	86	84
362	118	116	113	111	111
364	70	69	66	65	65