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# **Towards Sustainable and Efficient Road Transportation: Development of Artificial Intelligence Solutions for Urban and Interurban Mobility**

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## Abstract

The transportation of people and goods is both a complex problem and an essential service in modern society. Among the various modes of transportation, road transport offers unique advantages and challenges, thanks to its flexibility and operation in both urban and interurban areas. The growing social concern for the environment also affects road transportation, as motor vehicles are a major source of greenhouse gas emissions. However, the digitalisation of society and the emergence of new transport models indicate the potential for improvement in transportation, which could be better adapted to its users while operating in a more sustainable way.

In this thesis, we address the improvement of road transportation by means of computational techniques and artificial intelligence. This includes the modelling of transportation through multi-agent systems and their subsequent simulation. The operation of transportation fleets is determined by the distribution of tasks, the planning of the actions of each vehicle and their subsequent coordination. We explore different techniques and develop proposals that improve the operation of different transportation systems by considering three points of view: that of the operator, that of the user and, finally, that of sustainability. In other words, we aim to obtain systems with higher economic performance and quality of service while reducing their environmental impact.

The objective of improving road transportation is pursued on three fronts. First, a framework for the effective modelling and simulation of transportation systems is proposed. This contribution serves as a tool for the experimentation of the rest of the research. Next, the research focuses on urban transportation, a use case for which we model the city as a shared resource scenario. We propose the use of decentralised vehicle fleets for greater reactivity of the system. Through self-interested modelling, vehicles are incentivised to provide a better service to users while avoiding resource congestion. Finally, with the intention of bringing innovative solutions also to rural areas, our previous proposals are adapted to the use case of rural interurban transportation. In this case, we note the need for flexible and user-friendly public transportation, with special emphasis on its economic sustainability. Our system proposals follow these principles following the demand-responsive transportation paradigm.

The results of this thesis provide practical solutions for the enhancement of different road transportation systems, contributing to a future of more sustainable and user-tailored flexible mobility. As a contribution to the field of artificial intelligence the developed techniques have the potential to be adapted to fields beyond transportation, providing general solutions for the task allocation and the coordination of distributed elements.



## Resumen

El transporte de personas y bienes supone un problema complejo a la vez que un servicio esencial en la sociedad moderna. Entre los distintos modos de transporte, el transporte rodado supone ventajas y retos únicos, gracias a su flexibilidad y operación tanto urbana como interurbana. La creciente preocupación social respecto al medio ambiente afecta también al transporte rodado, pues los vehículos a motor son una gran fuente de emisiones de gases de efecto invernadero. Sin embargo, la digitalización de la sociedad y la aparición de nuevos modelos de transporte indican el potencial de mejora del transporte rodado, que podría adaptarse mejor a sus usuarios a la vez que operar de forma más sostenible.

En esta tesis afrontamos la mejora del transporte rodado mediante técnicas de computación e inteligencia artificial. Esto incluye el modelado de sistemas de transporte mediante sistemas multiagente y su posterior simulación virtual. La operación de las flotas de transporte está determinada por la distribución de tareas, la planificación de las acciones de cada vehículo y su posterior coordinación. Exploramos distintas técnicas y desarrollamos propuestas que mejoran la operación de distintos sistemas de transporte rodado considerando tres puntos de vista: el del operador, el del usuario y, finalmente, el de la sostenibilidad. En otras palabras, apuntamos a obtener sistemas con mayor rendimiento económico y calidad de servicio a la par que un reducido impacto medioambiental.

El objetivo de la mejora del transporte rodado se lleva a cabo desde tres frentes. Primero, se propone un marco de trabajo para el modelado efectivo y la simulación de sistemas de transporte. Esta aportación nos sirve como herramienta para la experimentación del resto de la investigación. Después, la investigación se centra en el transporte urbano, caso de uso para el que modelamos la ciudad como un escenario con recursos compartidos. Proponemos el uso de flotas de vehículos descentralizados para una mayor reactividad del sistema. Mediante un modelado de autointerés, se incentiva a los vehículos a proveer de un mejor servicio a los usuarios a la vez que evitan la congestión de los recursos. Finalmente, con la intención de aportar soluciones innovadoras también a las áreas rurales, se adaptan nuestras propuestas previas para el caso de uso del transporte rural interurbano. En este caso, observamos la necesidad de transporte público flexible y adaptado a los usuarios, con especial importancia en su sostenibilidad económica. Nuestras prop-

uestas de sistema siguen estos principios atendiendo al paradigma del transporte adaptable a la demanda.

Los resultados de esta tesis aportan soluciones prácticas para la mejora de distintos sistemas de transporte rodado, contribuyendo a un futuro de movilidad flexible más sostenible y adaptada al usuario. Como aportación en el ámbito de la inteligencia artificial, las técnicas desarrolladas tienen el potencial de ser adaptadas a campos más allá del transporte como soluciones generales para la distribución de tareas y la coordinación de elementos distribuidos.

## Resum

El transport de persones i béns suposa un problema complex alhora que un servei essencial en la societat moderna. Entre els diferents modes de transport, el transport rodat suposa avantatges i reptes únics, gràcies a la seua flexibilitat i operació tant urbana com interurbana. La creixent preocupació social respecte al medi ambient afecta també al transport rodat, doncs els vehicles de motor són una gran font d'emissions de gasos d'efecte d'hivernacle. No obstant això, la digitalització de la societat i l'aparició de nous models de transport indiquen el potencial de millora del transport rodat, que podria adaptar-se millor als seus usuaris alhora que operar de forma més sostenible.

En esta tesi afrontem la millora del transport rodat mitjançant tècniques de computació i intel·ligència artificial. Això inclou el modelatge de sistemes de transport mitjançant sistemes multiagent i la seua posterior simulació virtual. L'operació de les flotes de transport està determinada per la distribució de tasques, la planificació de les accions de cada vehicle i la seua posterior coordinació. Explorem diferents tècniques i desenvolupem propostes que milloren l'operació de diferents sistemes de transport rodat considerant tres punts de vista: el de l'operador, el de l'usuari i, finalment, el de la sostenibilitat. En altres paraules, apuntem a obtenir sistemes amb major rendiment econòmic i qualitat de servei al mateix temps que un reduït impacte mediambiental.

L'objectiu de la millora del transport rodat es duu a terme des de tres fronts. Primer, es proposa un marc de treball per al modelatge efectiu i la simulació de sistemes de transport. Esta aportació ens serveix com a eina per a l'experimentació de la resta de la investigació. Després, la investigació se centra en el transport urbà, cas d'ús per al qual modelem la ciutat com un escenari amb recursos compartits. Proposem l'ús de flotes de vehicles descentralitzats per a una major reactivitat del sistema. Mitjançant un modelatge d'autointerés, s'incentiva als vehicles a proveir d'un millor servei als usuaris alhora que eviten la congestió dels recursos. Finalment, amb la intenció d'aportar solucions innovadores també a les àrees rurals, s'adapten les nostres propostes prèvies per al cas d'ús del transport rural interurbà. En este cas, observem la necessitat de transport públic flexible i adaptat als usuaris, amb especial importància en la seua sostenibilitat econòmica. Les nostres propostes de sistema segueixen estos principis atés el paradigma del transport

adaptable a la demanda.

Els resultats d'esta tesi aporten solucions pràctiques per a la millora de diferents sistemes de transport rodat, contribuint a un futur de mobilitat flexible més sostenible i adaptada a l'usuari. Com a aportació en l'àmbit de la intel·ligència artificial, les tècniques desenvolupades tenen el potencial de ser adaptades a camps més enllà del transport com a solucions generals per a la distribució de tasques i la coordinació d'elements distribuïts.

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**Part I**

**Introduction and Objectives**



## Chapter 1

---

# Introduction and Objectives

---

*“The most important step a man can take. It’s not the first one, is it? It’s the next one. Always the next step, Dalinar.” – Quote from the novel Oathbringer, by Brandon Sanderson [132]*



Modern dictionaries define "transportation" as the action or process of transporting -carrying, conveying, or moving- things or persons from one place to another. Although technically correct, this definition may lead the reader to oversimplify the phenomenon we understand today as transportation. This study focuses on road transportation, which is performed between but also inside human settlements. Road transportation is contextualised within society and occurs as a crucial part of people's lives. Its infrastructure is entangled with our cities and landscapes; its operation influences our decisions. The use of transportation systems requires the coordination of several parties and has a tangible effect on the population it serves. Recognising its critical role in our society, this thesis focuses on improving road transportation and its consequent social enhancement. Transportation systems are redefined as resource -vehicles, stations- distribution problems for which solutions are proposed through computing and artificial intelligence techniques.

## **1.1 Characterising Transportation Enhancement**

Transportation systems are characterised by several features, as illustrated in Figure 1.1. A transportation mode comprises the type of vehicles employed to carry passengers or goods, the mobile elements of transportation. The infrastructure is the physical support of a transportation mode, generally composed of the vehicle fleet and a series of fixed elements such as routes and stations. The network is defined as a system of linked locations that provide the transportation system's functional and spatial organisation. Finally, the demand flow, or simply flow, constitutes the movement of a specific volume of passengers, goods, or information, with a particular frequency, over the network, associating it with an origin, several intermediate locations, and a destination.

Let us consider a public urban bus service as an example of a road transportation system. Such a service would use bus transportation as its mode, with an infrastructure supported by the bus station, bus stops and the routes assigned to each vehicle, a network conformed by the urban roads, and a demand flow described by the people making use of the service at each instant of the service hours.

Having defined transportation, assessing how computer science research approaches its optimisation is pertinent. Most authors consider two often conflicting

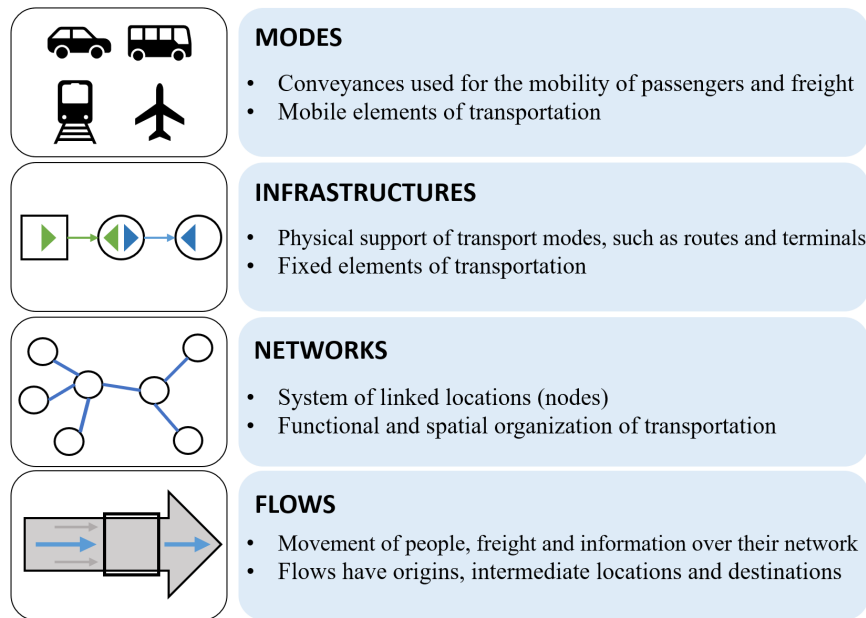


Figure 1.1: Core Components of Transportation. Image extracted and adapted from [126].

optimisation perspectives: that of the transportation operator and that of the user. On the one hand, the operator aims for the economic sustainability of the service. Their perspective is reflected in decreasing costs and boosting benefits while preserving an acceptable service quality. On the other hand, the user perspective focuses on their experience when using the service. User experience comprises the reliability of the service, better frequency, adaptability to specific user needs and, generally, a reduction in passenger waiting and travelling times. Although they are not opposing, as the operator benefits from satisfying its service users' needs, it can be seen how both perspectives are conflicted: a cut in costs may imply worsening service quality, whereas boosting passenger experience may increase operator expenses.

During this thesis's development, we found research focusing on a single of the above perspectives. However, the more comprehensive works considered both perspectives as their optimisation objective, thus formulating a multi-objective approach that generally leads to a trade-off between operational costs and passenger experience. Finally, more recent works consider a third perspective: the environmental impact of the transportation service. This perspective, often referred to as

the sustainability [67] of the service, is again conflicted with the operator's and the user's perspective. Sustainability concerns the direct and indirect effects on the environment the transportation service has, for instance, carbon dioxide emissions or traffic congestion. The inclusion of sustainability in the multi-objective formulation implies the inclusion of the context in which the transportation system is deployed in the optimisation efforts. In other words, emphasis is placed on transport's effect on society, not only on its operators and users.

Although they may be conflicting, all three perspectives (operator, user, and sustainability) have synergies, often meaning that aiming to improve one will also lead to improvements in another. As an example, let us consider enhancing a transportation system from the user's perspective, seeking that its operation is better adapted to the actual demand of the serviced area. The research may reveal that the transportation line servicing the area could be replaced by a single on-demand vehicle with a flexible route. Implementing this change would imply lower operational costs, as a whole line is replaced by a single vehicle; less pollution, as the vehicle would only travel if there was any demand; and, finally, a better service to the citizens of that area. With one modification, all three perspectives could be improved. This illustrates how considering all three perspectives may enrich road transportation optimisation research and lead to globally better results.

In this thesis, road transportation is improved by formulating transportation as a specific type of resource allocation problem [35, 167]. From a general perspective, resource allocation comprises assigning a certain amount of resources to a particular task. Establishing parallelism with the transportation domain, we consider the system's fleet and infrastructure as resources to assign, whereas the displacement demand defines the tasks [88], the travel services requested by users. The most straightforward application of this modelling considers the vehicle fleet as a set of resources [11]. In this sense, the operator's perspective can be improved by allocating vehicles more cost-effectively to travel requests. In contrast, the user's perspective can be enhanced by an assignment that reduces waiting and travelling time, for instance. However, other types of transportation infrastructure can also be considered as resources. For example, a set of electric charging stations may represent resources allocated to vehicles that need to recharge their batteries [72]. In this case, optimised allocation can lead to energy savings and thus lower the environmental impact of the transportation system.

## 1.2 Artificial Intelligence for Transportation

The field of artificial intelligence (AI) provides tools for solving complex problems in barely any domain. When it comes to transportation, there is a subset of AI techniques that have particular relevance to dealing with its associated challenges.

For the modelling of transportation systems, we introduce software agents [66], computer programs that aim to reproduce typically human values such as autonomy and reactive and social behaviour. Among them, we find a specification in intelligent agents [159] which can perceive their environment, and plan and execute concrete actions that modify the environment to achieve a specific goal. Intelligent agents are often part of multi-agent systems [160], where they interact with each other and with their shared environment. Multi-agent systems permit studying the interaction of various types of agents -often having different capabilities and goals- in a particular environment. These interactions may bring crucial insights into the research of individual problems or fields.

Road transportation, as defined previously, poses a complex problem with many actors, and that is often divided into concrete subproblems. Because of that, transportation (as a research field) and multi-agent systems (as an AI technique) are a perfect match. The so-called agent-based modelling (ABM) [56] is a computational model for simulating the actions and interactions of autonomous agents, aiming to understand the behaviour of a system and what governs its outcomes. Following the principles of ABM [13], the transportation network is represented by the shared environment of the multi-agent system. Each actor -vehicles, users, managers and even parts of the infrastructure- can be encoded into an intelligent agent, together with their actions and goals. Finally, the system's flow is determined by the agent's behaviours and interactions. This scenario provides the ideal breeding ground for studying, developing, and validating techniques to enhance transportation.

ABM can also be defined as a software simulation with intelligent agents as its building blocks [90]. Software simulations are processes that represent real-world events through mathematical formulas. A simulation allows the user to observe the execution and outcome of the reproduced phenomenon in a virtual environment without actually performing it. In addition, such an environment can be tailored to study specific effects. The improvement of a transportation service generally in-

volves modifications over its network, infrastructure, or operation. These changes, in turn, have an impact on all involved actors as well as society. Because of that, simulations are of the utmost importance for testing and validating transportation improvement techniques [19, 25], ensuring the reliability of a change before implementing it in the real world.

Once a transportation system is modelled, its improvement comes from the development of its operation. Such an operation can be split into three tasks: allocating travel requests to fleet vehicles, scheduling each vehicle's actions, and coordinating the execution of such actions. An essential part of the system's organisation is the component that will be in charge of solving the above tasks [149]. If a single component is in command, we model a centralised operation [78]. In this case, the other system actors will receive instructions from the governing component. In contrast, actors can be given some autonomy, allowing their own goals to be reflected in their actions. This describes a decentralised system [44]. At the technical level, the difference between these organisational models lies in the location where the algorithms are implemented and the flow of communication between the different elements.

Several techniques exist to build solutions for the request-vehicle assignments, vehicle scheduling and fleet coordination tasks. A classic technique is automated planning. Planning algorithms receive as input a set of goals, a set of possible actions, and the current state of the environment in which the agents operate. The output then returns a list of actions to be performed in the environment to achieve the predefined goals. This powerful technique can solve an entire transportation system, either through a centralised planner or in a distributed manner, allowing each vehicle to plan its actions. However, due to its high computational complexity, planning may not be suitable for solving reactive systems operating in real-time.

Beyond classical AI, a recent study [2] reviews different techniques that have been applied to the field of transportation. These belong to specific areas within AI such as machine learning [145], metaheuristics [43], game theory [49], and fuzzy logic [143]. Machine learning is concerned with developing and studying statistical algorithms that can effectively generalise and thus perform tasks without explicit instructions. Metaheuristic techniques aim to provide sufficiently good solutions to optimisation problems, especially with incomplete information or limited computation capacity. Game theory studies mathematical models that repre-

sent strategic interactions among rational decision-makers. Finally, fuzzy logic is based on the observation that people make decisions based on imprecise and non-numerical information, enabling the representation of models that work with vague data.

The research carried out in this thesis's framework has used ABM to model transportation systems, multi-agent systems to implement them and simulation to experiment with them. The proposed systems define centralised or decentralised operation according to the needs of the area where they will be deployed. Finally, the improvement techniques developed come from machine learning, planning, game theory and heuristics. Each chapter carefully characterises these intelligent techniques for a better understanding of the contributions.

## 1.3 Motivation

The research conducted in this thesis has been carried out as a response to the current needs in the road transportation of goods and services [119], which is becoming increasingly complex. Those needs must be balanced with the environmental impact of the transportation itself to produce practical solutions that are up to European Union standards on sustainability [76]. We propose the use of artificial intelligence (AI) techniques as a tool to model, study and improve road transportation systems, considering their operational costs, service quality, and social/environmental impact.

With the previous transportation characterisation, we have outlined the magnitude that the improvement of road transportation involves. Nevertheless, it is typical for research works in AI techniques for transportation enhancement to focus on a single aspect or process of the system. The outcome of these studies tends to lack the proper insight into the practicality and applicability of their proposals. In this thesis, we theorise that a broader viewpoint towards transportation optimisation achieves more practical solutions. Because of that, our research approaches the distribution of resources of transportation systems and tackles their optimisation on three fronts, which are reflected in the selected papers.

First, we focus on transportation data generation and simulation. The changes introduced to a transportation system have a profound impact on the system's oper-

ation and the society in which the transportation system is integrated. It is therefore crucial to test and analyse such changes before their implementation in a real-world system. For that, two ingredients are needed. On the one hand, we need input data that reflects the functioning of the transportation system with as much detail as possible. On the other hand, we need a simulation tool to virtually reproduce the transportation system and experiment with it, assessing the likely impact of all introduced changes.

To deal with both challenges mentioned above, our thesis project has been supported by SimFleet [117], a multi-agent-based simulator, which enabled us to test our proposals on many occasions. The simulator has been upgraded according to our needs throughout the research development. Synthetic data generators have been implemented, allowing us to create more realistic simulations in a straightforward way. These generators produce agent movement for our simulations based on real-world data from the area where the transportation research takes place. More informed simulations bring better quality results and, in turn, more relevant insight into the topic at hand.

Second, the attention was driven to road transportation within cities. Urban transportation occurs in a densely connected and dynamic environment, with high volumes of displacement demand. In addition, new transportation paradigms are spreading. Among the many new services, for this part, we focus on people and goods transportation performed by open fleets [16], such as those of enterprises like Uber or Cabify. Open fleets are composed of independent vehicles that deal with their own goal while providing a global service. These features make open fleets dynamic and reactive to changes but introduce their own challenges to their coordination.

Given the features of open fleets, our research goes beyond traditional centralised transportation to explore innovative systems and coordination algorithms. On the one hand, we propose a coordination by consensus algorithm for self-interested agents. Self-interested agents act according to their private goals but are interested in coordinating their operations with other parties to avoid conflicts. On the other hand, we further model transportation with this type of agent by making a demand-responsive transportation (DRT) system proposal that provides services with an open fleet.

The potential and flexibility we observed in the DRT paradigm brought us to

the third front: the extension and adaptation of our previous proposals to the rural transportation field. Rural areas have been historically disregarded for innovation compared to their urban counterparts. These areas present their own set of characteristics that require a redesign of transportation algorithms for a better chance of solving them adequately. Rural and interurban road transportation presents longer distances to cover, less densely connected networks and a spatially distributed demand. With all of these in mind, we explored the application of DRT to develop quality rural public road transportation.

The first step of applying DRT to rural settlements was a deep dive into previous work and learned lessons regarding rural transportation. That included a detailed characterisation of DRT and rural transportation demand and an assessment of failed and successful proposals over time. Then, our own system was proposed, finally testing a hands-on implementation of rural DRT.

The work performed during this thesis constitutes a transversal approach to road transportation enhancement through AI and asset -vehicles, passengers, stations-distribution techniques. The development of a simulation framework allowed the subsequent experimentation with specific road transportation systems and optimisation techniques. The presented research has been contextualised and supported by the research projects *Intelligent techniques for optimising the location for electric vehicle recharging stations and improving mobility in cities* (SP20180184), *Towards Smart and Sustainable Mobility Supported by Multi-Agent Systems and Edge Computing* (RTI2018-095390-B-C31-AR), *Coordinated Intelligent Serviced for Adaptive Smart Areas* (PID2021-123673OB-C31), and a research stay at the Faculty of Organisation and Informatics, University of Zagreb, in Croatia.

The initial financial support for the project was provided by the *Universitat Politècnica de València* under grant PAID-01-20-4, from March to September 2021. The main financial support has been provided by the *Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital de la Generalitat Valenciana*, under grant ACIF/2021/259, from October 2021 and until the project's completion.



## 1.4 Objectives

Considering the motivation stated above, the main objective of our research is the development of intelligent solutions for the improvement of road transportation from the operator, user, and sustainability perspectives. This is, the achievement of faster, more reliable and cost-effective transportation services that incur less environmental impact. Our work begins focusing on urban mobility systems. Then, the intention of extending our proposals to interurban mobility brings us to the enhancement of rural transportation services. All the research to be carried out in the above two areas requires, however, the creation of tools for the experimentation through simulation. Because of that, we propose the following division of the main objective into more specific sub-objectives.

1. Propose a framework for the effective modelling and experimentation of transportation systems.
  - 1.1 Classify the state-of-the-art techniques of multi-agent modelling and simulations.
  - 1.2 Develop synthetic data generation algorithms to introduce realistic agent movement in transportation simulations.
  - 1.3 Integrate the data generation algorithms with a multi-agent simulator and run complex experiments to validate the infrastructure.
  - 1.4 Model different road transportation systems and study their operation using the developed framework, assessing the results from the operator, user, and sustainability perspectives.
2. Propose intelligent solutions for the improvement of urban road transportation through the distribution of its assets.
  - 2.1 Analyse the state-of-the-art research on urban transportation improvement and identify open problems.
  - 2.2 Explore the different types of road transportation services for people and goods.

- 2.3 Define a resource-distribution-based urban transportation domain and create simulation scenarios set on it.
  - 2.4 Design and implement coordination techniques for a swift, conflictless and sustainable urban transportation service.
  - 2.5 Propose a flexible, sustainable, open-fleet-based urban road transportation service.
3. Extend and adapt the proposed solutions to the improvement and flexibilisation of interurban and rural road transportation.
    - 3.1 Analyse the state-of-the-art research on rural road transportation and identify research gaps.
    - 3.2 Assess the specific challenges that rural transportation systems face for their successful implementation.
    - 3.3 Adapt and implement algorithms for a dynamic operation of interurban rural transportation systems.
    - 3.4 Explore task-allocation techniques to improve the cost-effectiveness of dynamic interurban rural transportation systems.
    - 3.5 Propose a flexible, cost-effective rural and interurban public road transportation system.

## 1.5 Structure of the Thesis

This PhD thesis is structured into six parts as follows.

- **Part I: Introduction and Objectives.** The first part of this thesis presents the introduction and the motivation of the research work carried out, characterising the assessed topic. Moreover, we provide several listings comprising the research objectives, the academic publications, and research projects that supported this PhD thesis.
- **Part II: Transportation Simulation.** The second part of the thesis presents the contributions that address the first objective. These focus on the realistic

simulation of transportation fleets and the subsequent analysis of the results. Part II of this thesis is partially framed in the research project *Intelligent techniques for optimising the location of electric vehicle recharging stations and improving mobility in cities*.

**Chapter 2. Charging Stations and Mobility Data Generators for Agent-based Simulations** (*Selected paper*). Proposal and validation of several data generation algorithms for creating realistic transportation simulation scenarios.

**Chapter 3. Taxi Services and the Carsharing Alternative: A Case Study of Valencia City** (*Selected paper*). Sustainability-centred analysis of taxi services with respect to carsharing through multi-agent simulation.

- **Part III: Urban Transportation Enhancement.** The third part of the thesis groups the contributions that address the second objective. These works focus on the improvement of the operation and sustainability of urban road transportation. The proposed transportation systems are implemented by decentralised fleets of self-interested vehicles. Part III of this thesis is partially framed in the research project *Towards Smart and Sustainable Mobility Supported by Multi-Agent Systems and Edge Computing*.

**Chapter 4. Best-Response Planning for Urban Fleet Coordination** (*Selected paper*). Proposal of an original coordination procedure for self-interested transports belonging to an open fleet. This work proposes an architecture combining an ad-hoc optimal planning algorithm with a game-theoretic coordination process, proving its potential to both improve the fleet's operation and reduce resource consumption.

**Chapter 5. Demand-Responsive Shared Transportation: A Self-Interested Proposal** (*Selected paper*). First approach to demand-responsive transportation with the proposal of an adaptable infrastructure that coordinates the dynamic operation of a fleet of self-interested transports.

- **Part IV: Rural and Interurban Transportation Enhancement.** This part contains the contributions that address the third objective of the thesis. It presents research in the development of cost-effective and flexible rural road transportation. Algorithms and proposals that originated in the work of Part III are adapted to rural mobility, after a thorough assessment of its characteristics and needs. Part IV of this thesis is partially framed in the research project *Coordinated Intelligent Services for Adaptive Smart Areas*.

**Chapter 6. A Survey on Demand-responsive Transportation for Rural and Interurban Mobility** (*Selected paper*). Literature review on research specifically dealing with demand-responsive transportation systems operating on rural settlements. This work fully characterises demand responsive and the needs of rural mobility. The analysis of previous articles brings crucial insight regarding the economic viability of these systems.

**Chapter 7. A Flexible Approach for Demand-Responsive Public Transport in Rural Areas** (*Selected paper*). Proposal of an architecture for the implementation of a rural-specific demand-responsive transportation service. This work includes the development of a scheduling algorithm that finds passenger-vehicle assignments following a system-wide, user-defined optimisation function.

- **Part V: Discussion.** This part elaborates a discussion of the research results that make up the thesis project. In it, we highlight the value of our proposals, explaining how they contribute to the fields of transportation simulation, enhancement of urban transportation and improvement of rural transportation.
- **Part VI: Conclusions and Future Work.** Finally, this last part of the thesis summarises the motivation for the project and the work carried out. It then presents conclusions on the results and theorises on possible future directions that the research in this project could take.

## 1.6 List of Publications

The work done in this thesis is supported by several publications. Following, we list these contributions classified by their type. Note that those publications marked with (\*) are included in this document.

- Journals listed in JCR (publications ordered by impact factor):
  - Jaume Jordán, **Pasqual Martí**, Javier Palanca, and Vicente Julian. Electric vehicle charging stations emplacement using genetic algorithms and agent-based simulation. *Expert Systems with Applications*, Volume 197, 116739, 2022, doi: 10.1016/j.eswa.2022.116739. *Impact Factor*: 8,5 (Q1)
  - (\*) **Pasqual Martí**, Jaume Jordán, Javier Palanca, and Vicente Julian. Charging Stations and Mobility Data Generators for Agent-based Simulations. *Neurocomputing*, Volume 484, pages 196-210, 2022, doi: 10.1016/j.neucom.2021.06.098. *Impact Factor*: 6 (Q2)
  - Jaume Jordán, **Pasqual Martí**, Javier Palanca, and Vicente Julian. Interurban charging station network: An evolutionary approach. *Neurocomputing*, Volume 529, pages 217-221, 2023, doi: 10.1016/j.neucom.2023.01.068. *Impact Factor*: 6 (Q2)
  - (\*) **Pasqual Martí**, Jaume Jordán, and Vicente Julian. Best-response planning for urban fleet coordination. *Neural Computing and Applications*, 2023, doi: 10.1007/s00521-023-08631-9. *Impact Factor*: 6 (Q2)
  - (\*) **Pasqual Martí**, Jaume Jordán, and Vicente Julian. A Survey on Demand-responsive Transportation for Rural and Interurban Mobility. *International Journal of Interactive Multimedia and Artificial Intelligence*, Volume 8, Number 3, pages 43-54, 2023 doi: 10.9781/ijimai.2023.07.010. *Impact Factor*: 3,6 (Q3)
  - (\*) **Pasqual Martí**, Jaume Jordán, Fernando De la Prieta, Holger Billhardt, and Vicente Julian. Demand-Responsive Shared Transportation:

- A Self-Interested Proposal. *Electronics*, Volume 11, Issue 1, 78, 2022, doi: 10.3390/electronics11010078. *Impact Factor*: 2,9 (Q3)
- Holger Billhardt, Alberto Fernández, **Pasqual Martí**, Javier Prieto Tejedor, and Sascha Ossowski. Towards the Prioritised Use of Transportation Infrastructures: The Case of Vehicle-Specific Dynamic Access Restrictions in City Centres. *Electronics*, Volume 11, Issue 4, 576, 2022, doi: 10.3390/electronics11040576. *Impact Factor*: 2,9 (Q3)
  - **Pasqual Martí**, Jaume Jordán, Fernando De la Prieta, and Vicente Julian. Optimization of Rural Demand-Responsive Transportation through Transfer Point Allocation. *Electronics*, Volume 12, Issue 22, 4684, 2023. doi: 10.3390/electronics12224684. *Impact Factor*: 2,9 (Q3)
  - (\*) **Pasqual Martí**, Jaume Jordán, Pablo Chamoso, and Vicente Julian. Taxi services and the carsharing alternative: a case study of valencia city. *Mathematical Biosciences and Engineering*, Volume 19, Issue 7: 6680-6698, 2022, doi: 10.3934/mbe.2022314. *Impact Factor*: 2,6 (Q2)
  - (\*) **Pasqual Martí**, Jaume Jordán, and Vicente Julian. A flexible approach for Demand-Responsive Public Transport in rural areas. *Computer Science and Information Systems*, 2023. doi: 10.2298/CSIS230115074M. *Impact Factor*: 1,4 (Q4)
- International conferences (articles ordered chronologically ascending):
    - **Pasqual Martí**, Jaume Jordán, Javier Palanca, and Vicente Julian. Load Generators for Automatic Simulation of Urban Fleets. In *Highlights in Practical Applications of Agents, Multi-Agent Systems, and Trustworthiness. The PAAMS Collection*, (PAAMS 2020), pages 394-405, 2020, doi: 10.1007/978-3-030-51999-5\_33.
    - **Pasqual Martí**, Jaume Jordán, Javier Palanca, and Vicente Julian. Free-Floating Carsharing in SimFleet. In *Intelligent Data Engineering and Automated Learning – IDEAL 2020*, pages 221–232, 2020, doi: 10.1007/978-3-030-62362-3\_20.

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- **Pasqual Martí**, Jaume Jordán, Fernando De la Prieta, Holger Billhardt, and Vicente Julian. Infrastructure for the Enhancement of Urban Fleet Simulation. In *Sustainable Smart Cities and Territories*, (SSCTIC 2021), pages 263-273, 2021, doi: 10.1007/978-3-030-78901-5\_23.
  - Holger Billhardt, Alberto Fernández, Sandra Gómez-Gálvez, **Pasqual Martí**, Javier Prieto Tejedor, and Sascha Ossowski. Reducing Emissions Prioritising Transport Utility. In *Sustainable Smart Cities and Territories*, (SSCTIC 2021), pages 300-311, 2021, doi: 10.1007/978-3-030-78901-5\_26.
  - Jaume Jordán, **Pasqual Martí**, Javier Palanca, Vicente Julian, and Vicente Botti. Interurban Electric Vehicle Charging Stations Through Genetic Algorithms. In *Hybrid Artificial Intelligent Systems* (HAIS 2021), pages 101-112, 2021, doi: 10.1007/978-3-030-86271-8\_9.
  - **Pasqual Martí**, Jaume Jordán, and Vicente Julian. Carsharing in Valencia: Analysing an Alternative to Taxi Fleets. In *Highlights in Practical Applications of Agents, Multi-Agent Systems, and Social Good. The PAAMS Collection*, (PAAMS 2021), pages 270-282, 2021, doi: 10.1007/978-3-030-85710-3\_23.
  - **Pasqual Martí**, Jaume Jordán, and Vicente Julian. Demand Responsive Mobility for Rural Areas: A Review. In *Highlights in Practical Applications of Agents, Multi-Agent Systems, and Complex Systems Simulation. The PAAMS Collection*, (PAAMS 2022), pages 129-140, 2022, doi: 10.1007/978-3-031-18697-4\_11.
  - **Pasqual Martí**, Jaume Jordán, Fernando De La Prieta, and Vicente Julian. Dynamic Transfer Point Allocation for Rural Demand-Responsive Mobility. In *Trends in Sustainable Smart Cities and Territories*. (SSCT 2023), pages 453-464, 2023, Springer, Cham, doi: 10.1007/978-3-031-36957-5\_39.
  - **Pasqual Martí**, Jaime Llopis, Vicente Julian, Paulo Novais, and Jaume Jordán. Validating State-Wide Charging Station Network Through Agent

Based Simulation. In *Highlights in Practical Applications of Agents, Multi-Agent Systems, and Cognitive Mimetics. The PAAMS Collection*, (PAAMS 2023), pages 158-169, 2023, Springer, Cham, doi: 10.1007/978-3-031-37593-4\_13

- Bogdan Okreša Durić, Tomislav Peharda, and **Pasqual Martí**. Towards a Gamified System to Influence Behaviour of Users in the Context of Smart Mobility. In the proceedings of the *34th Central European Conference on Information and Intelligent Systems (CECIIS)*, pages 9-16, 2023, University of Zagreb. Available online at: <http://archive.ceciis.foi.hr/app/index.php/ceciis/index/pages/view/ProceedingsArchive2023>

## 1.7 Research Projects

The research work presented in this thesis was carried out in the context of the following research projects.

- Intelligent techniques for optimising the location of electric vehicle recharging stations and improving mobility in cities
  - *Funder*: Universitat Politècnica de València (SP20180184)
  - *Lead Applicant*: Jaume Jordán
  - *Years*: 2019 - 2020
- Towards Smart and Sustainable Mobility Supported by Multi-Agent Systems and Edge Computing
  - *Funder*: Agencia Estatal de Investigación (RTI2018-095390-B-C31-AR)
  - *Lead Applicant*: A. Giret and V. Julian
  - *Years*: 2020 - 2022
- Coordinated Intelligent Services for Adaptive Smart Areas (COSSAS)



- *Funder:* Agencia Estatal de Investigación (PID2021-123673OB-C31)
- *Lead Applicant:* C. Carrascosa and V. Julian
- *Years:* 2022 - 2025

## 1.8 Research Grants

The following research grants provided financial support for the development of the work presented in this thesis.

- Predoctoral contract for the training of doctoral students of the Universitat Politècnica de València
  - *Funder:* Universitat Politècnica de València (PAID-01-20-4)
  - *Lead Applicant:* Pasqual Martí Gimeno.
  - *Years:* 2021 - 2021
- Grants for the recruitment of pre-doctoral research staff
  - *Funder:* Generalitat Valenciana and European Social Fund (ACIF/ 2021/ 259)
  - *Lead Applicant:* Pasqual Martí Gimeno.
  - *Years:* 2021 - 2025

**Part II**

**Transportation Simulation**



# Charging Stations and Mobility Data Generators for Agent-based Simulations

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### Abstract

*Current traffic congestion and the resulting carbon emissions are two of the main problems threatening the sustainability of modern cities. The challenges facing today's cities focus primarily on the optimisation of traffic flow and the transition to electric vehicles. The latter aspect implies the need for an adequate deployment of the infrastructure of charging stations. The inherent complexity in today's cities and the difficulty in implementing new policies whose benefits are difficult to measure and predict has led in recent years to consider the enormous potential of simulation tools and in particular of the agent-based simulation (ABS). ABS allows the specification of complex models that reflect the complexity and dynamism of urban mobility. Current technology in ABS has evolved and matured sufficiently to provide very sophisticated tools but lacking facilities for a flexible and realistic generation of input data in the execution of the experiments. In line with this, this paper introduces two configurable generators that automatise the creation of experiments in agent-based simulations. The generators have been developed with the SimFleet simulation tool enhancing the simulation of realistic movements and location of vehicles, passengers and other users of the urban traffic system within a city. The generators proved to be useful for comparing different distributions of locations as well as different agent movement behaviours based on real city data.*

## 2.1 Introduction

The International Telecommunication Union (ITU) and the United Nations Economic Commission for Europe (UNECE) defined, in 2015, a smart sustainable city as an innovative city that uses Information and Communication Technologies (ICTs) to improve quality of life, the efficiency of urban operations and services, and competitiveness, while ensuring that it meets the needs of present and future generations concerning economic, social, environmental and cultural aspects. Currently, the list of challenges for keeping current cities sustainable has grown, and consequently, so has the need to establish appropriate intervention policies with the lowest possible risk.

One way of researching how to deal with such challenges is through the use of simulators [112], and specifically agent-based simulation (ABS) [38]. ABS integrates an interesting number of properties which makes it useful for a wide range of domains, supporting structure preserving modelling of the simulated reality, parallel computations, simulation of proactive behaviour, and flexible and dynamic simulation scenarios [31]. All these properties can be clearly observed in the domain of today's cities, where we find multiple autonomous entities that move around the city and make use of a collection of resources located according to certain policies, such as policies for the deployment of new electric vehicle charging stations. Currently, we can find a multitude of agent-based simulation tools [1], some of them specifically designed for traffic or urban mobility management. Using these tools, it is possible to see the effect that the changes would have on the city after defining them, thus avoiding a possible unsuccessful deployment. However, as current cities are very complex systems, it is necessary to have a complete simulator that allows experimentation with big and complex configurations inside the city. The more realistic the simulator, the more accurate and useful experiments would be for real-world applications.

In this work, we propose different ways to generate more realistic data as input for agent-based simulation experimentation, extending a previous work presented in [98]. More specifically, we focus the processes of generating more realistic data on two problems: the generation of possible locations for electric vehicle charging stations, and the generation of realistic movements of entities in a city to have an appropriate representation of its traffic flow. To do this, we use SimFleet simulator

[117], which is able to place different varieties of agents with custom behaviours over real-world cities to develop and test any type of strategies. Over SimFleet we have developed two generators for the above commented problems. On the one hand, a charging stations generator to create several distributions of these infrastructures, and make comparisons and simulations with well-informed charging stations emplacing systems such as the one in [71], which uses several data sources to feed a genetic algorithm that obtains solutions. On the other hand, a mobility data generator of entities that move in a city such as delivery transports, private vehicles, or taxi fleets, among others. Moreover, these mobility data generators makes use of real data of the city, which implies a more informed approach to the generation of realistic traffic in a city to be used in dynamic simulations. To do this, different generators of each type have been developed, where the most sophisticated ones are based on different AI techniques and are explained in detail further in this paper.

In order to illustrate the use of the proposed generators, the paper includes a case study in the city of New York, concretely in the Manhattan Island area. The study has been made using available data such as population, traffic, and tweets, from open data portals, or gathered with other tools like U-tool [33].

The rest of this paper is structured as follows. Section 2.3 presents the SimFleet simulator, on which the proposal presented in this paper has been developed. Sections 2.4 and 2.5 explain the two main generators proposed in this work, that is, the charging stations simulator and the mobility data generator. Section 2.6 illustrates through a case study the use of the proposed generators. Finally, some conclusions are presented in Section 2.7.

## 2.2 Related Work

Agent-based simulation has become in recent years a key aspect for the development of more realistic simulations with high scalability. In the environment of urban mobility, there are many works that try to perform simulations to study aspects such as traffic, movement of citizens, crowds, emergency situations, or the optimal location of different services.

To support the modelling and development of these simulations, different tools

have been appearing that facilitate the execution of experiments for the study of mobility both at urban and interurban level. A review on agent-based simulation tools for traffic and transportation can be consulted in [10].

In traffic simulation, one of the most well-known tools is SUMO [12]. SUMO is an open-source traffic simulation framework which includes net import and demand modelling components. SUMO helps in several research topics such as traffic light algorithm, the choice of routes, and in the simulation of vehicular communication with other vehicles or with the infrastructure. The framework is used in different projects to simulate traffic management or autonomous driving. SUMO employs origin/destination matrices to describe the movement between traffic assignment zones in vehicle number per time in large-scale scenarios. Moreover, SUMO can be extended through new applications in order to extend how to generate traffic information for the simulation process.

Another well-known simulation framework is MATSim [155]. MATSim is a framework that allows the implementation of large-scale agent-based transport simulations. The framework is mainly employed for demand-modelling and traffic flow simulation. MATSim offers several extensions which enhance the functionality with additional features, one example is the package that allows to convert Google Transit Feed Specification (GTFS) data into a MATSim transit schedule. The GTFS is an extension of the General Transit Feed Specification which is a data specification that allows public transit agencies to publish their transit data in a format that can be consumed by a wide variety of software applications. Other example we can highlight is SIMmobility [4], which is a simulation framework that helps in the prediction of the impact of mobility demands on intelligent transportation services, vehicular emissions and transportation networks, or its specific version for logistics called SimMobility Freight [131]. VISSIM [45] is another well-known commercial simulator that provides an ecosystem of products that can be integrated to provide solutions to solve different mobility and transportation challenges. VISSIM is the only one that offers real-time knowledge acquisition. Lastly, Matisse 3.0 [146] is the last version of a microscopic simulator for agent-based intelligent transportation systems which includes intersection controllers and enables V2X and I2I [87] communication mechanisms.

Another widely used framework is AnyLogic<sup>1</sup>. AnyLogic is a general purpose simulation software but includes specific extensions for mobility management that allows to simulate aspects such as transportation planning, fleet management, and traffic flow. As facilities for data generation, AnyLogic allows the import of databases as well as the generation from scratch of different components of the simulation. There exists numerous examples of mobility simulation models in AnyLogic, in [104] a simulation model is used as a decision support tool for estimating efficiency of vehicle schedules with time windows. Another example is the work presented [162] which is a study of passenger flow in urban subway stations which makes use of the Anylogic pedestrian library.

From another perspective, new agent-based simulators for the generation and testing of autonomous driving strategies have recently appeared. These simulators are based more on providing mechanisms for sensing, monitoring, communication and action at the level of autonomous vehicles in order to provide solutions for the problem of autonomous driving. One of the best-known examples is CARLA<sup>2</sup> [37]. CARLA allows controlling aspects such as traffic generation, pedestrian behaviours, weathers and vehicle sensors. Its main goal is to allow the learning of new driving policies or the training of new perception algorithms. Other similar simulation frameworks are AIRSim<sup>3</sup> [137] (a simulator developed by Microsoft as a platform to experiment with AI learning algorithms), TORCS<sup>4</sup> [161] (an Open Racing Car Simulator which is an open source 3D car racing simulator that is designed to enable AI-based strategies for competing drivers), and in [139] an urban traffic simulation framework is presented for helping the development and test of automated driving vehicles.

As can be observed there exist different agent-based simulation tools that offer several facilities for the generation of highly accurate simulations with high scalability. However, most of these tools do not offer specific facilities for a flexible and realistic generation of input data in the simulation. Usually, the analysed approaches incorporate the possibility of generating third-party software or simply include database import modules. Accordingly, in our proposal we make use of

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<sup>1</sup><https://www.anylogic.com>

<sup>2</sup><http://carla.org>

<sup>3</sup><https://microsoft.github.io/AirSim/>

<sup>4</sup><https://sourceforge.net/projects/torcs/>



different approaches, including AI techniques, that make use of real-world data as input to improve simulations both by positioning elements, such as electric charging stations, in a more informed way, and by generating new, more realistic input data, such as the most feasible traffic routes.

## 2.3 Extending the SimFleet Simulator

SimFleet [117] is a simulator based on SPADE [115] (a multi-agent system development environment) specialised in testing different mobility strategies where vehicles that belong to different fleets interact in the simulation. This simulation tool has been chosen because of its features. It allows you to manage simulated fleets in an easy and very flexible way. This is thanks to the agent architecture provided by the SPADE platform, which allows every actor in the simulation to be a proactive and independent agent which can have its own strategy and behaviour. Also, scaling the simulation is simple. In SimFleet each simulation counts for a number of clients (Customer agents), transport operators (Transport agents) and fleet managers (FleetManager agents), where Customer agents serve individuals who need to be shipped from their place of origin to their place of destination in the region. In order to do so, each Customer agent demands a single transport service offered by the Transport agent. Then, it is the duty of the FleetManager agent to get the clients in need of a transport service and the transport providers that might be required to provide such services into touch. In short, the FleetManager agent serves as a command and control centre for transports. It acknowledges the incoming customer requests and forwards those requests to the relevant transport providers.

For passenger transportation across the region, SimFleet uses the OSRM<sup>5</sup> routing software to locate the shortest routes in the road network. A query to OSRM receives the origin and destination points and returns the shortest route between the two points.

A SimFleet user needs to develop the behaviour of each agent in the simulation in order to define their negotiation policy. Throughout this research we have ignored the development and testing stages in order to concentrate on the simulation

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<sup>5</sup><http://project-osrm.org/>

development, a function in which much of this sort of simulators have limitations, as presented in the related work.

We must clarify how the experiments are represented in order to understand the limitations of SimFleet in conjunction with the development of simulations. To load a simulation into SimFleet the user must write a JSON file where the details of each actor of the simulation (this is, the agents) are described (position, initial data, goals, etc.). These parameters may vary depending on the type of agent.

The only way to fill in the configuration file at the moment is to build each agent manually, providing values to their attributes. This presents a problem for developing simulations with a huge amount of vehicles, consumers or packages. In addition, SimFleet is likely to be used by users to replicate static elements such as charging (or gas) stations and movements around a city in a simulated environment. On the one side, it may be of interest for urban planners to measure how each distribution can influence the mobility of the city by using a generator to put charging (or gas) stations in different configurations. Mobility modelling, on the other hand, involves introducing several agents that appear in the system during the simulation time, as well as the mobility information of agents around the area, based on real data measured from the city. Via the implementation of generators that simplify the development of simulation configurations, our work intends to solve those needs.

Two global generators are the key contribution of this work, enabling the setup of larger and more realistic simulations with SimFleet. The generators are an instrument not only for helping the user write big files, but also for creating realistic configuration files based on the actual target city details. These informed generators are designed to produce configuration files that are as similar to reality as possible (i.e. simulating vehicles mobility with real traffic data from the city).

The first generator is a generator for charging stations that populates the simulation area with a defined number of charging stations following a specified template. The second generator is a mobility data generator that fills the simulation space with various types of moving agents that can be pseudo-random or informed. In addition, in order to compare informed versions against them, entirely random versions of both generators were also introduced.

Next sections present these two generators in depth. First we present the charging stations generator, which allows selecting different approaches (from less in-

formed to more informed) to place stations in the city map. Next, a mobility data generator is presented, which allows to create realistic movements along the city map.

## 2.4 Charging Stations Generator

The charging stations generator is in charge of placing a certain number of charging (or petrol) stations in the city according to a certain technique or distribution. The generator has the following main parameters:  $n$  charging stations to place;  $p$  charging poles to locate in the stations; and distribution type,  $\{random, uniform, radial, genetic\}$ , that determines the technique used to place the stations in the city. The first three types of distributions correspond to non-informed charging station generators, i.e. they only use the parameters of the number of charging stations and poles to be placed on the city map according to the specified distribution (*random*, *uniform*, or *radial*). However, the so-called *genetic* distribution uses information about the city (population, traffic, and activity in social networks) to distribute the charging stations by means of a genetic algorithm that optimises utility and cost.

The charging stations generator receives the number of charging poles as an input parameter. The charging poles are the spots that can be used by a vehicle in a charging stations, so a station consist of at least a charging pole. In the *genetic* distribution, the genetic algorithm receives as parameter the maximum charging poles per station, and hence, it allocates the charging poles  $p$  in the specified  $n$  stations depending on the utility and cost that the complete distribution provides. However, the *random*, *uniform*, and *radial* distributions allocate one pole in each station, and the remaining poles are placed using one of the following alternatives:

- In the first case, the list of stations is shuffled and the poles are distributed following the order of the list. This process is repeated shuffling again the list until all poles are distributed.
- The second case makes a pseudo-random distribution that allocates the remaining poles by selecting a random station and placing a random amount of poles in it. However, the random number of poles is limited to a percentage of the total poles to avoid uneven distributions.

The output of the charging stations generator is a GeoJSON file with the position and number of poles of each station. However, the position given by the generator is processed using the *getValidPoint* function of the service *nearest* of OSRM, which obtains a valid point situated in a street near the given coordinates. In the case of the genetic algorithm, this process is performed before to ensure that the set of Points of Interest (PoIs) that have to be provided to the genetic algorithm (it must be an amount of PoIs significantly larger than the stations to place) are already valid.

### 2.4.1 Random Distribution

This distribution generates a set of  $n$  valid points in the city map that will be the positions of the charging stations. For each point, coordinates  $x$  and  $y$  are randomly generated within the bounds of the city map defined by its polygon:  $x_{min}$ ,  $y_{min}$ ,  $x_{max}$ ,  $y_{max}$ . The valid point of these coordinates is obtained and if it is not inside the city map, it is discard. So, until there are  $n$  valid points, this process is repeated.

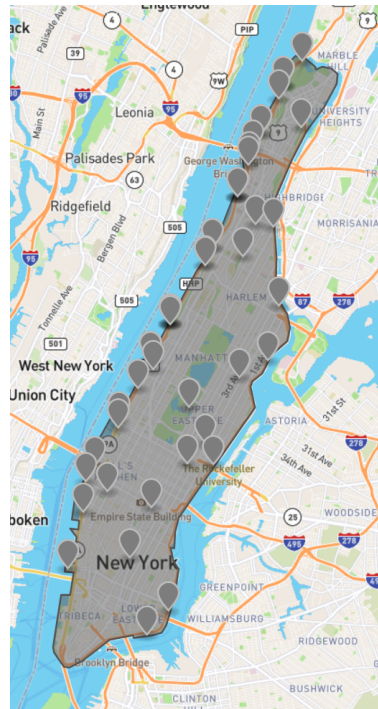


Figure 2.1: Random distribution of stations.

Algorithm 1 shows a pseudo-code which operates as described. In addition, an example of a random distribution with 50 stations in Manhattan is shown in Figure 2.1. A random distribution is useful to serve as a baseline for comparisons with other more informed distributions.

---

**Algorithm 1** Allocates  $n$  stations in random points within the *city\_map*

---

**Require:** *city\_map*,  $n$   
 $valid\_points \leftarrow []$   
 $x_{min}, y_{min}, x_{max}, y_{max} \leftarrow city\_map.bounds()$   
**while**  $length(valid\_points) < n$  **do**  
     $(x, y) \leftarrow randomPoint(x_{min}, y_{min}, x_{max}, y_{max})$   
    **if**  $city\_map.contains((x, y))$  **then**  
         $valid\_points \leftarrow valid\_points \cup (x, y)$   
    **end if**  
**end while**

---

## 2.4.2 Uniform Distribution

In this distribution, the city map (Figure 2.2a) is divided uniformly<sup>6</sup> into rectangular cells of equal size. The *grid* (see Figure 2.2b) is a wider working area created from the bounds of the city map with the points of the polygon  $\{(x_{min}, y_{min}), (x_{min}, y_{max}), (x_{max}, y_{max}), (x_{max}, y_{min})\}$ .

The grid size can be obtained depending on the amount of stations ( $n$ ) as specified in Equation 2.1. The number of rows and columns will be the square root if  $n$  is a perfect square. Otherwise, there will be more rows or more columns if the grid is higher or wider.

$$(2.1) \quad \begin{cases} rows = cols = \sqrt{n} & n \text{ is perfect square} \\ rows = \lfloor \sqrt{n} \rfloor, cols = \lceil \sqrt{n} \rceil & height < width \\ rows = \lceil \sqrt{n} \rceil, cols = \lfloor \sqrt{n} \rfloor & otherwise \end{cases}$$

---

<sup>6</sup>The name ‘‘Uniform distribution’’ does not refer to a probability distribution but to how stations are divided in the city map.

Nevertheless, as the shape of the city map can be very irregular and a significant part of the grid may be outside the boundaries, the user can also define the number of rows and columns to find a more suitable cell distribution instead of using the method of Equation 2.1.

Once the grid has been obtained, it is trimmed with respect to the city map and the cells outside the borders are discarded as in Figure 2.2c. The cells of the grid are traversed and a station is placed in the nearest valid point to the centroid of the cell. In the case of any remaining stations to be distributed, they would be placed at random valid points within randomly selected cells. Figure 2.2d shows an example of this distribution and Algorithm 2 describes its operation by means of pseudo-code.

There is an alternative version of this distribution in which all stations are directly placed in randomly chosen cells at a random valid point.

---

**Algorithm 2** Distributes  $n$  stations uniformly within the *city\_map*

---

**Require:** *city\_map*,  $n$

*valid\_points*  $\leftarrow$  []

$x_{min}, y_{min}, x_{max}, y_{max} \leftarrow city\_map.bounds()$

*grid*  $\leftarrow Polygon(x_{min}, y_{min}, x_{max}, y_{max})$

*grid*  $\leftarrow grid \cap city\_map$

**for all** *cell* in *grid* **do**

$(x, y) \leftarrow cell.centroid()$

*valid\_points*  $\leftarrow valid\_points \cup (x, y)$

**end for**

# Place leftover station in random points inside random cells

**while**  $length(valid\_points) < n$  **do**

*cell*  $\leftarrow randomCell(grid)$

$(x, y) \leftarrow randomPoint(cell)$

*valid\_points*  $\leftarrow valid\_points \cup (x, y)$

**end while**

---

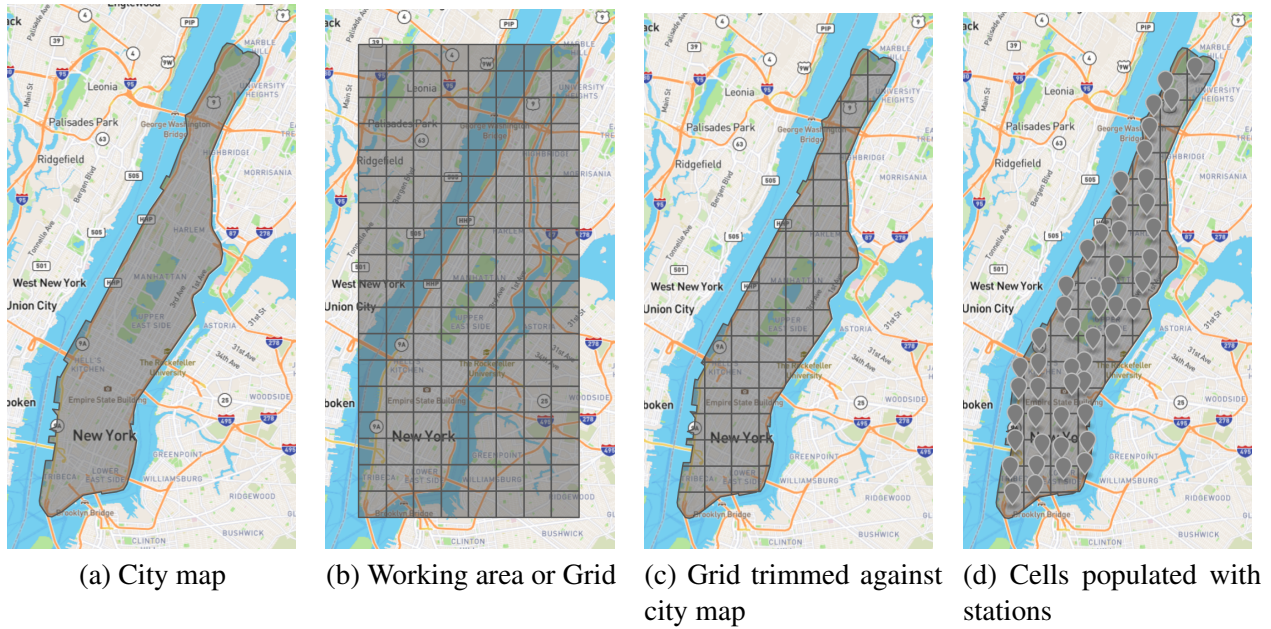


Figure 2.2: Uniform distribution of stations process.

### 2.4.3 Radial Distribution

The radial distribution aims to adapt the charging station infrastructure to certain urban areas which present greater activity towards its centre in contrast to the outskirts. It makes use of a new parameter  $c$ , which defines the number of circles in which the city map will be divided.

The distribution procedure begins by defining two copies of a wider working area, created as detailed for the uniform distribution. The first copy gets divided into a configurable number of triangles, 8 by default, as it is shown in Figure 2.3a. These are created by joining the working area vertex and sides' middle points with the centroid of the city map. As for the second copy, it gets partitioned by  $c$  concentric circles, each with a larger radius than the previous. The initial radius  $r$  is calculated according to the dimensions of the map. Each circle gets trimmed against its previous one, starting with the last (and larger) created, so as to avoid overlap among them. The resulting polygons are also trimmed against the city map, obtaining an area with a central circle and many outer rings, as shown in Figure 2.3b. Bear in mind that we will be referring to both circles and rings just as circles from now on. Finally, the two modified areas are intersected, dividing each



circle into up to 8 parts, obtaining a city map similar to that shown in Figure 2.3c.

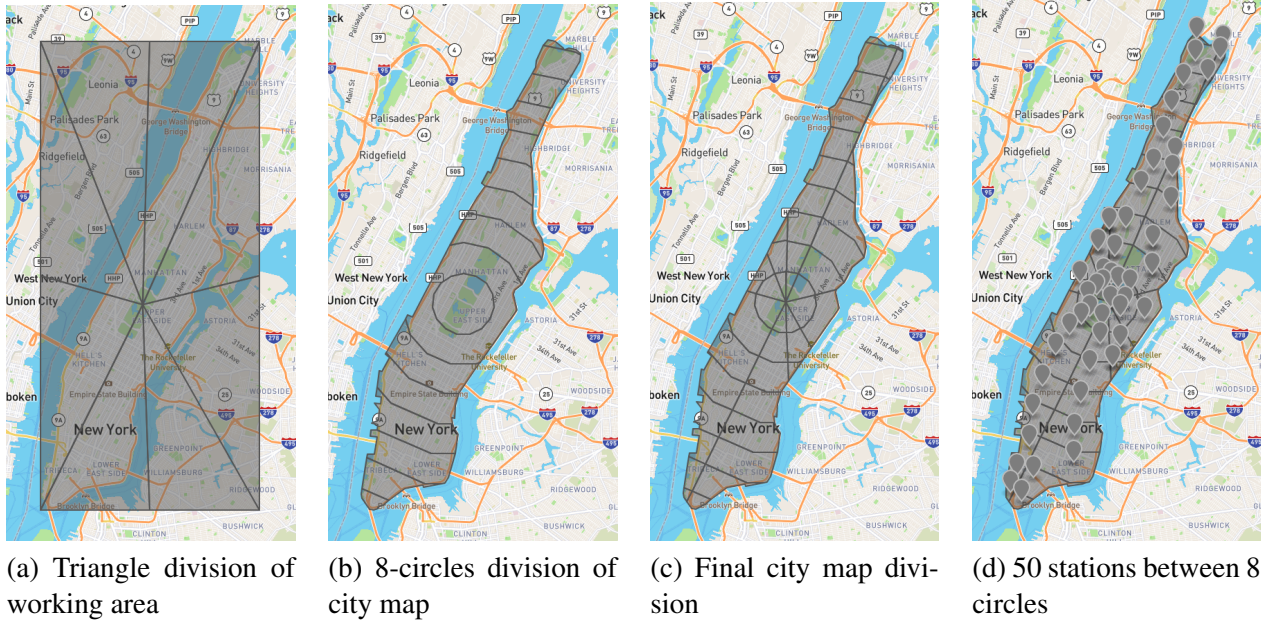


Figure 2.3: Radial distribution of stations process.

Stations are assigned to the nearest valid point to the centroid of the polygons. To assign the stations as evenly as possible among each circle and the city map, both the number of stations per circle ( $n/c$ ) and the subdivisions a circle has are taken into account. Each triangle is populated beginning from the inner circle and heading towards the outer. Once a station has been allocated to all polygons of a triangle, the next triangle will be picked with respect to the number of stations and the total number of subdivisions to evenly spread the stations within a circle. This process is described by Algorithm 3. An example of a finished distribution is shown in Figure 2.3d.

The procedure explained above allocates only one station inside each polygon. However, there may be a higher number of stations to allocate than polygons in the map, as the granularity of the division is decided by the user. For such cases, the leftover stations are positioned by arbitrary selecting a polygon and a valid point inside it.

A completely random variant of this distribution has also been introduced. The city map is split in the same manner and the ratio of stations per circle is considered



as well. The allocation of stations, however, is performed in random valid points of arbitrary subdivisions of each circle.

---

**Algorithm 3** Distributes  $n$  stations following a radial pattern with  $c$  circles within the *city\_map*

---

**Require:** *city\_map*,  $n$ ,  $c$ , *num\_triangles*

```

valid_points  $\leftarrow$  []
x_min, y_min, x_max, y_max  $\leftarrow$  city_map.bounds()
working_area  $\leftarrow$  Polygon(x_min, y_min, x_max, y_max)
triangle_area  $\leftarrow$  divideInTriangles(working_area, num_triangles)
circle_area  $\leftarrow$  divideInCircles(working_area,  $c$ )
working_area  $\leftarrow$  triangle_area  $\cap$  circle_area  $\cap$  city_map #Calculate the
number of stations to place in each circle
stations_per_circle  $\leftarrow$   $\lfloor n/c \rfloor$ 
while length(valid_points) <  $n$  do
    triangle  $\leftarrow$  triangleSelection(stations_per_circle, num_triangles) #Select
next triangle to populate
    for all cell in triangle do
        (x, y)  $\leftarrow$  cell.centroid()
        valid_points  $\leftarrow$  valid_points  $\cup$  (x, y)
    end for
end while
#Place leftover station in random points inside random cells
while length(valid_points) <  $n$  do
    cell  $\leftarrow$  randomCell(grid)
    (x, y)  $\leftarrow$  randomPoint(cell)
    valid_points  $\leftarrow$  valid_points  $\cup$  (x, y)
end while

```

---

### 2.4.4 Genetic Algorithm Distribution

An alternative to placing charging stations or petrol stations in a city in an intelligent way is to use genetic algorithms. Thus, this option of the generator is based on the genetic algorithm presented in the papers [75, 116]. In the previous *random*,

*uniform*, and *radial* alternatives, the only necessary data are the map itself and the city limits together with the number of charging poles to be placed. This has the advantage that if no more data is available, a set of stations in the city can also be generated following the chosen distribution, which in some cases may be sufficient. However, these approximations may be unrealistic to the reality of the city, since a uniform or radial distribution may not correspond to the actual distribution and movements of the potential users of the stations.

Thus, when relevant data from the city is available the solution that the genetic algorithm can provide might be more realistic. Particularly, these data must be referred to the possible users of the stations. Hence, the data considered relevant to obtain the most accurate solution are:

- **Population or cadastral information:** It shows the amount of people that live in different zones of a city. The population information ( $P$ ) is defined as:  $P = \{(C_1, p_1), (C_2, p_2), \dots, (C_n, p_n)\}$ , where  $C_i$  is a closed polygon representing a zone in the city together with its population  $p_i$ .
- **Traffic information:** It shows the number of vehicles moving around a certain area. The traffic information ( $T$ ) is defined as:  $T = \{(R_1, t_1), (R_2, t_2), \dots, (R_n, t_n)\}$ , where  $R_i$  is a polyline that follows a street or road indicating the volume of traffic  $t_i$ .
- **Twitter activity:** Information about the amount of geo-located tweets, from the social network Twitter, tweeted from a certain location. This information can be used to determine where a representative percentage of the population is spending their time. The Twitter activity ( $A$ ) is defined as:  $A = \{(Q_1, a_1), (Q_2, a_2), \dots, (Q_n, a_n)\}$ , where  $Q_i$  is a point represented as a latitude-longitude tuple and  $a_i$  the number of tweets in such coordinates.

The sum of the population, traffic and activity data of the area covered by each of the charging poles ( $cp$ ) of a solution or individual ( $ind$ ) defines the utility of the solution. In addition, each of the data is balanced by a weight  $\omega$  to give it more or less importance.

$$(2.2) \quad utility(ind) = \sum_{\forall cp_i > 0 \in ind} (p_i \cdot \omega_P + t_i \cdot \omega_T + a_i \cdot \omega_A)$$

On the other hand, the distribution of charging stations in a city also implies high costs, so this becomes an additional criterion for the optimal distribution of charging stations. Therefore, the data to take into account in relation to costs are: cost of each station  $c_s$  and charging pole  $c_{cp}$  (additional charging pole to a station have a lower cost than the installation of the first point/station), cost per distance to transformer substation  $c_{dt}$ , and positions of transformer substations.

$$(2.3) \quad cost(ind) = \sum_{\forall cp_i > 0 \in ind} c_s + (cp_i \cdot c_{cp}) + (distenergy(s) \cdot c_{dt})$$

Considering the population, traffic and social network data, that is, the utility of placing charging stations, and the costs of placing them according to their position and number, the genetic algorithm obtains a solution in which it optimises its fitness function, which is formed by the utility and cost. Since this is a multi-criteria optimisation, the genetic algorithm tries to obtain the maximum utility and the minimum cost to place the required charging stations and points.

The process of the genetic algorithm to generate the set of charging stations in the city is detailed below.

Firstly, the genetic algorithm starts from a set of Points of Interest (PoIs) that must be provided. This set of PoIs must be considerably larger than the number of stations to be placed so the genetic algorithm can select the final subset where the charging stations will be placed, and thus make sense for its application in this context. The set of PoIs can be specified by the user, or on the contrary, it can be created using different types of points such as those extracted from open data of the city of study. The set of PoIs provided defines the individual of the genetic algorithm, which is an array with the length of the set of PoIs. Then, each position of the array represents each PoI in the city, and the integer number inside will be the amount of poles to install in the PoI. This number can be from 0 to the maximum poles per station specified by the user. Therefore, the genetic algorithm generates different individuals simply by changing the integer numbers of the array and evaluating the fitness of each of them.

Secondly, all possible geographical data (in GeoJSON) must be provided so that the genetic algorithm can obtain informed solutions: cadastral data specified in number of inhabitants by areas or polygons ( $P$ ); traffic data specifying a number for each street (at least the main roads) ( $T$ ); geo-located activity in social networks ( $A$ );

and transformer substations. In addition, the weights  $\omega$  with which the cadastral, traffic and social network activity information is valued can be provided, along with the monetary costs per station ( $c_s$ ), per charging pole ( $c_{cp}$ ), and per distance to the transformer substation ( $c_{dt}$ ).

Finally, the genetic parameters themselves such as the initial population of individuals and number of generations must be provided. In this case, the higher the values, the greater the exploration of the genetic algorithm will be; however, its computing time will also increase. These are some parameters that should be tested with low values in order to increase them according to the execution times. In our case, as the computation of fitness is relatively complex, we can start from 100 population and 50 generations, which should be computed in minutes at most. In addition, the probabilities of crossover and mutation, together with their operators, can be specified, however, the default values for this generator should be enough (see [116] for more information).

With all the parameters specified above, it is possible to run the genetic algorithm that will provide a distribution of charging stations in the city that is as optimal as possible with respect to fitness, i.e. maximising the value of the utility, and minimising the cost values. An example of 50 stations placed in Manhattan with the genetic distribution is represented in Figure 2.4. This figure shows both the location of the stations within the boundaries of the city map, as well as the Voronoi polygons that determine the areas of influence (along with a 300-meters radius circular area that intersects the Voronoi polygon) of each of the stations.

In this section, different charging station generators have been presented. The first generators, corresponding to the *random*, *uniform*, and *radial* distributions, serve as a baseline or for situations when no city data is available. On the other hand, the generator based on the genetic algorithm, i.e., the distribution that we have named as *genetic*, has all the available information of the city where it is applied. This means that the charging station distribution solutions obtained by the genetic-based generator are potentially more realistic, that is, adapted to the demand for this type of service in the city. A detailed example of the genetic-based charging stations generators is shown in Section 2.6.1.

In addition, the electric vehicle charging station (or petrol station) generators presented in this section could also be used as a method for deciding the location of other types of services, either fixed or dynamic. For example, any other type of

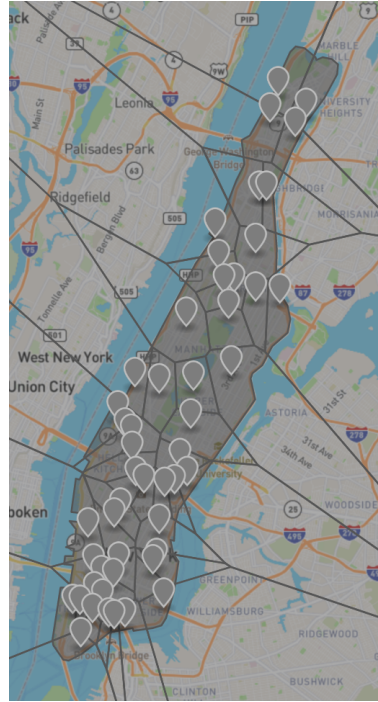


Figure 2.4: Genetic distribution of stations example.

infrastructure such as bicycle stations or taxi ranks, as well as distribution of ambulances or emergency services, positioning of open-fleet vehicles or car-sharing services, among others.

## 2.5 Mobility Data Generator

With the mobility data generator, we aim to create either random or real-life inspired movement of agents for SimFleet’s simulations. To generate realistic movement data, from the point of view of an agent-based simulator, means to create movements around the city which are inspired by its citizens and other users of the traffic system such as private vehicles, taxi fleets, etc. This movement can be adapted to any of the agent types that SimFleet offers by creating routes for them which have their origin and destination points located in certain areas of the city in which there is more activity. Both the areas and the type of activity are dependent on the data source we use. For instance, we could have data indicating the amount of population in a specific neighbourhood at a precise time of the day; sim-

ilarly, we could gather the number of delivery vehicles that depart from a certain zip code area at a certain weekday. There are many possibilities and depending on data availability one could apply the principles of our generator to create mobility data for different situations.

Hereunder are presented random and informed versions of the mobility data generator. The random version simply creates valid routes and assigns them to the agents. The informed versions of the mobility data generators, which create realistic routes, are inspired by the work in [50], which presents an approach based on the creation of a mobility graph with real traces.

The mobility data generator develops routes of at least *min\_dist* meters long for *n* agents of type *t* within the borders of a given city map. The delay parameter *d* determines the point of the simulation in which the agents will start their execution; by default, at the beginning of the simulation ( $d = 0$ ). The number of agents per batch, *agents\_per\_batch*, is introduced to give different delays to groups of agents that will start executing simultaneously. This is most useful for scenarios with a great number of agents. If indicated, the first batch of agents will have a delay of *d* seconds; the following batch, a delay of  $2d$ , and so on. As indicated above, all generators are prepared to receive an existing SimFleet configuration file as input and fill it with agent definitions and their routes. This enables the use of the mobility data generator to introduce, in the same simulation, different types of agents in diverse quantities, with different delays and batch sizes, achieving a complex simulation scenario.

### 2.5.1 Random Movement Generator

The movement of the random generator is created by designating a random route (random origin and destination points) for the agents to follow. Both the origin and destination points must be valid points inside the city map, and they must be a minimum of *min\_dist* meters apart. This process is repeated to create and assign routes for *n* agents of type *t*. The origin point indicates the agent the location in which it will spawn, whereas the destination point determines the place where the execution will finish. Transport type agents can travel by themselves. However, if the agent is of customer type or a package, the movement will actually be performed by the transport agent that carries it after picking it up.

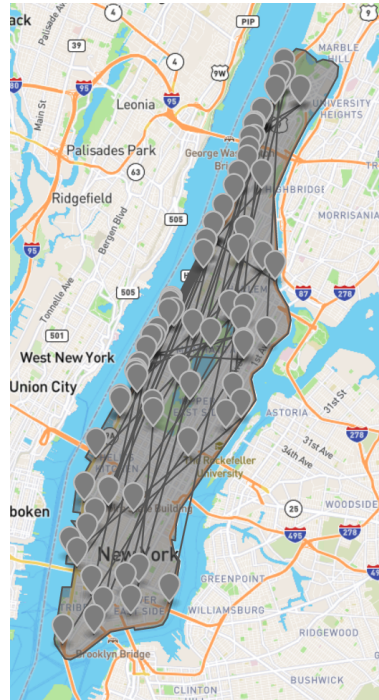


Figure 2.5: 50 randomly generated routes in Manhattan, indicated by a line connecting origin and destination points.

## 2.5.2 Informed Movement Generator

The mobility data generator’s informed variant attempts to replicate more accurate movements across the city map. For this, it is important to provide relevant data to the generator on which to base the agents’ routes. This data can be accessed from different sources; often open data portals the government of a city or nation provides to its inhabitants. For our generator, we used the following data (already presented in Section 2.4.4): population or cadastral information ( $P$ ); traffic information ( $T$ ); and Twitter activity ( $A$ ).

The data is used to establish a probability distribution between a series of points available in the city map. The assignment of the routes’ origin and destination will be carried out according to the distribution. The process starts by generating a collection of available points. As described for the uniform distribution (see Section 2.4.2), the city map ( $M$ ) is split as a grid obtaining  $M = \{(G_1, O_1), (G_2, O_2), \dots, (G_n, O_n)\}$ ; where  $G_i$  is a closed polygon and  $O_i$  the closest valid point to the centroid of  $G_i$ . The grid is divided by a configurable number



of rows and columns. Such a number directly affects the granularity of the system, as a larger number of cells implies more accessible points (see Figure 2.6). The more points, the more distributed will be the probability.

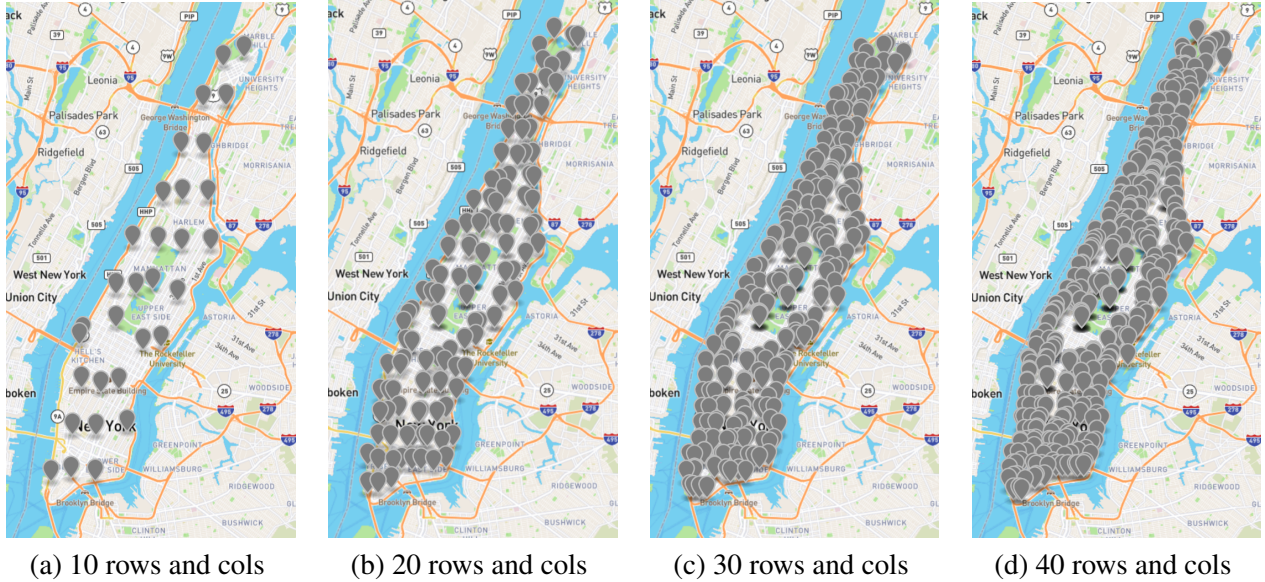


Figure 2.6: Number of available points according to map division granularity.

By combining the city data with  $M$ , we join, for every polygon  $G_i$ , the population, traffic and Twitter activity volumes that occur inside its area:  $M = \{(G_1, O_1, \{p_1, t_1, a_1\}), (G_2, O_2, \{p_2, t_2, a_2\}), \dots, (G_n, O_n, \{p_n, t_n, a_n\})\}$  and compute the likelihood associated with each point  $O_i$  as in Equation (2.4):

(2.4)

$$prob(O_i) = w_p \cdot \frac{p_i}{\sum_{j=1}^n p_j} + w_t \cdot \frac{t_i}{\sum_{j=1}^n t_j} + w_a \cdot \frac{a_i}{\sum_{j=1}^n a_j}; \text{ with } w_p + w_t + w_a = 1$$

where  $w_p$ ,  $w_t$  and  $w_a$  are weights that control the effect on the probability of each of the variables. By having  $w_p + w_t + w_a = 1$  we obtain a probability distribution among points that ensures that the addition of the probability of each point is equal to 1. An intuitive example of this can be seen in Table 2.1 and Equation 2.5. Finally, the set of available points ( $S$ ) and their resulting probabilities:  $S = \{(O_1, p(O_1)), (O_2, p(O_2)), \dots, (O_n, p(O_n))\}$ ; are taken into account for route generation.



Table 2.1: Example of a probability distribution among 3 points. \*Value obtained according to Equation 2.5.

Point ( $O_i$ )	Population in $O_i$ ( $p_i$ )	Traffic in $O_i$ ( $t_i$ )	Activity in $O_i$ ( $a_i$ )	Probability ( $prob(O_i)$ )
$O_1$	5000	1500	3500	0.44625*
$O_2$	3700	4500	1000	0.39375
$O_3$	1300	2000	500	0.16
Total values	10000	8000	5000	<b>1.0</b>
Weights	0.5 ( $w_p$ )	0.3 ( $w_t$ )	0.2 ( $w_a$ )	

$$(2.5) \quad prob(O_1) = 0.5 \cdot \frac{5000}{10000} + 0.3 \cdot \frac{1500}{8000} + 0.2 \cdot \frac{3500}{5000} = 0.44625$$

When all points in  $S$  have an associated probability, the process to define the  $n$  routes starts (see Figure 2.7 for examples). The approach is very similar to the one described for the random mobility data generator, except this time the origin and destination points are picked from  $S$  with respect to their probability and guaranteeing the *min\_dist* between both points.

### 2.5.3 Regression Mobility Data Generator

The regression version of the mobility data generator creates a data model and makes use of it to enrich the simulations with a real-life inspired movement of agents.

In this work, using New York City as an example, we used the regression mobility data generator to reproduce a realistic taxi demand across the city map. For this, we employ the TLC Trip Record Data<sup>7</sup> of the city of New York. This dataset contains records of taxi services which are defined, among other parameters, by the service start date (month, day and time of the day) as well as an origin and destination taxi zone identifiers. With this information, we divided our simulation's city map into its corresponding taxi zones and created a regression model which

<sup>7</sup><https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page>

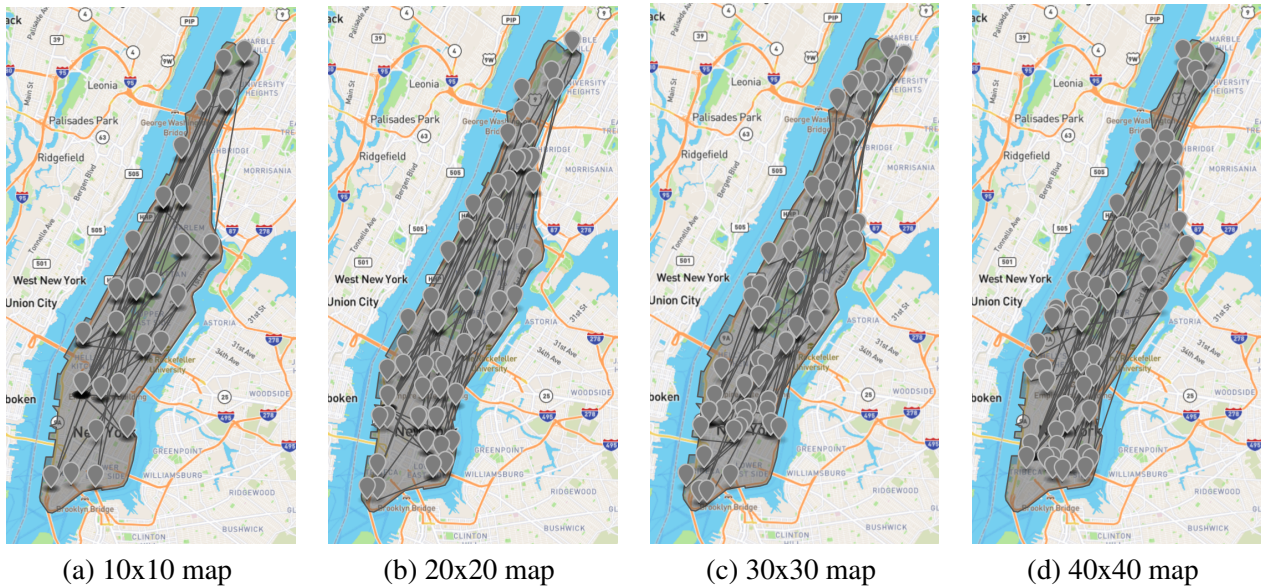


Figure 2.7: 50 routes examples in Manhattan with different granularity.

can estimate the amount of demand in each taxi zone for a specific month, week-day and time of the day. Please refer to Section 2.6.2 for a detailed explanation of how the data was processed.

Therefore, the generated movement is represented by a certain number of customer agents that will spawn distributed among the different taxi zones according to the predicted value of each zone. Additionally, as the dataset includes not only the origin but the destination taxi zone of each service, we can also estimate a service destination. According to the observed services, we can assign a probability to every taxi zone that indicates how likely it is to be the destination of a service originated in a specific taxi zone at a certain month, weekday and time of the day. By pseudo-randomly choosing a destination according to such probabilities, we complete the routes of the customer agents.

The customers will be picked up and driven to their destinations by transport agents. Consequently, we have generated mobility data which is in line with real-life taxi demand as well as origin and destination areas. Optionally, we could develop a relocation service for transport agents, using the same regression model, which sent idle taxis to zones where more demand is likely to appear in the next minutes or hours; although that is outside of the scope of this work, as it has more

to do with transport agent strategic behaviour.

As can be seen, we have designed and implemented three approaches to mobility data generation with different levels of complexity. The random movement generator may be useful to establish baseline measurements in simulations, so as to compare them against other systems. As for the more informed versions, they make use of real-world data, processing it with different techniques to create realistic routes. Assigning such routes to agents in our simulations we obtain a better representation of the real urban traffic system. The regression mobility data generator employs the most complete approach, although in a very general perspective, as it can be used with many types of input data. In the following Section 2.6.2 we illustrate the use of the latter generator with a detailed example.

## 2.6 Case Study

In this section, we present a case study on the island of Manhattan in order to illustrate the use of the charging stations generator as well as the mobility data generator described in Sections 2.4 and 2.5. Throughout the previous sections we have shown illustrative examples of how each of the generators works, i.e., each of the distributions of the charging stations generator (*random, uniform, radial, genetic*), and the mobility data generators (random, informed, and regression). Thus, in this case study we focus on what we can consider to be the most informed and potentially most realistic generator for each case. Thus, Section 2.6.1 details the use of the genetic algorithm-based charging station generator, and Section 2.6.2 details the use of the regression-based mobility data generator to generate a realistic demand for taxis in the Manhattan island.

### 2.6.1 Genetic Generation of Stations

In this section we present the use and results obtained from the charging stations generator based on the genetic algorithm of Section 2.4.4 on the case study located in Manhattan. Concretely, we specify the pre-processing of the Manhattan data as well as the parameters used to prepare the experimentation with the gener-

ator. Then, the results of executions with different number of charging stations are shown.

### 2.6.1.1 Data Pre-processing

One of the crucial parts for a successful operation of the charging stations generator based on the genetic algorithm is the data on which it is based. For the genetic algorithm we will use data on population, traffic, and social media activity (in this case, Twitter). The population and traffic data have been extracted from the New York open data portal<sup>8</sup>. Regarding the Twitter data, it has been obtained using uTool [33], a tool that captures geo-located tweets during a specific period of time.

The population data of Manhattan has been extracted from two different datasets. On the one hand, the 2010 Census tracts<sup>9</sup> are used as the division of different areas of Manhattan. Then, this data is processed and merged with the census demographics at the neighbourhood tabulation area (NTA) level<sup>10</sup>. Concretely, the number of population at 2010 of each NTA code from the last dataset is assigned to the corresponding polygon that defines the NTA (extracted from the first dataset). This produces a GeoJSON file with the population by areas of Manhattan (represented in Figure 2.8a) that can be provided to the genetic algorithm.

Regarding the traffic data of Manhattan, two different datasets have also been used. On the one hand, the New York City street centreline dataset<sup>11</sup> has been used for having the polylines that define the streets of Manhattan. On the other hand, the traffic volume counts from 2014 to 2019<sup>12</sup> have been used to have the number of cars moving through the streets of Manhattan. These data have been processed to establish a correspondence between the street names represented in both datasets, as there is no compatible identification or code that we can use for our needs. All traffic volume counts, which are separated by date and hour from

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<sup>8</sup><https://opendata.cityofnewyork.us/>

<sup>9</sup><https://data.cityofnewyork.us/City-Government/2010-Census-Tracts/fxpq-c8ku>

<sup>10</sup><https://data.cityofnewyork.us/City-Government/Census-Demographics-at-the-Neighborhood-Tabulation/rnsn-ac2>

<sup>11</sup><https://data.cityofnewyork.us/City-Government/NYC-Street-Centerline-CSCL-/exjm-f27b>

<sup>12</sup><https://data.cityofnewyork.us/Transportation/Traffic-Volume-Counts-2014-2019-/ertz-hr4r>

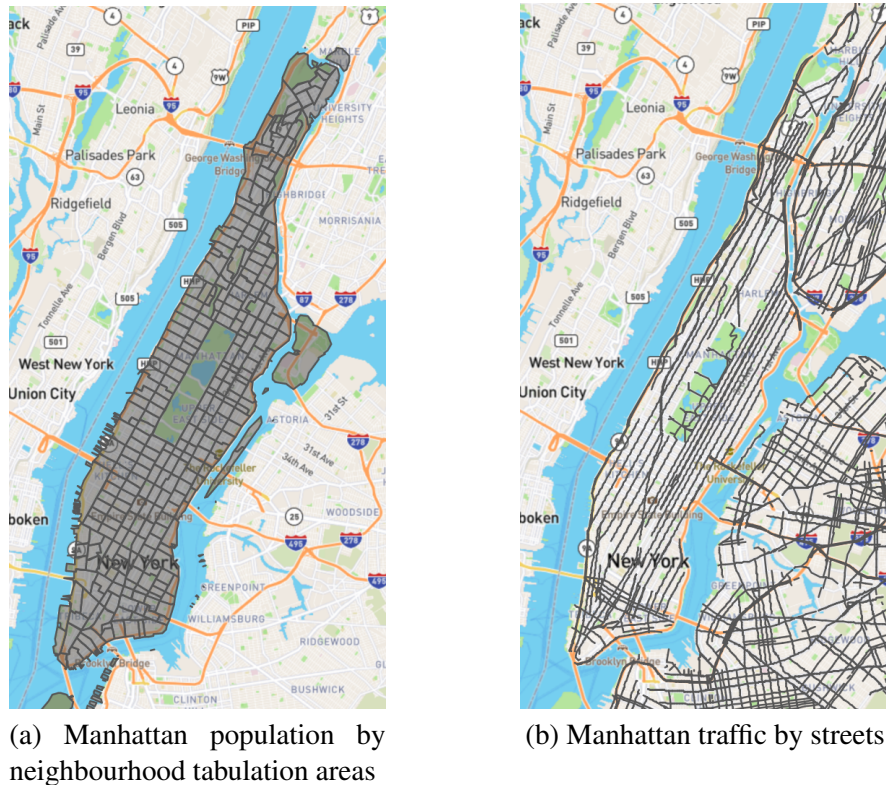


Figure 2.8: Manhattan population and traffic.

2014 to 2019 are aggregated to have a single number per street. This aggregation gives a global picture of the traffic volume in Manhattan that allows the genetic algorithm to discriminate between different streets or areas. All this process ends up with a GeoJSON file (represented in Figure 2.8b) which is ready to be used by the genetic algorithm.

The geo-located tweets to use with these experiments are from 2017 to 2019, that is, 3 complete years. The total number of geo-located tweets is roughly 4.5 million for New York City. However, this volume of data is difficult for the genetic algorithm to process, as it would be very slow for each of the solution evaluations. It is therefore more appropriate to reduce it by using the *geohash* system[111], which allows the encoding of a geographical location using a string of characters. In our case, the advantage lies in using a certain precision (7 characters) to reduce the 4.5 million points at which the tweets are located to a smaller set. Hence, all tweets that have the same geohash are grouped together in the same “bucket”, so

that we end up with a set of points that represent each of the geohashes with the number of tweets that have been made in that area. Thus, by applying geohash with precision 7 we reduce the 4.5 million tweets of New York City to 41194 geohash areas, and specifically, 5467 are the geohash areas corresponding to the island of Manhattan that group together around 1.8 million tweets.

The genetic algorithm needs to start from a set of points of interest (PoIs) in the city where it is applied. This set of PoIs must be considerably larger than the number of stations to be placed in order for the genetic algorithm to determine which combination of points is the most appropriate. In other words, if the set of PoIs were very similar to the number of stations to be placed, a genetic algorithm would not be necessary and could be obtained by brute force. For these experiments, we composed a set of 409 PoIs in the main isle of Manhattan which are separated at least 150 meters. These PoIs represent areas in which a charging station could be considered given their interest and the activity generated around them. Examples include existing petrol stations, museums, monuments, tourist attractions, cinemas or theatres, shopping areas, restaurants, among others.

The parameters used to configure the genetic algorithm to obtain the charging stations to be placed in Manhattan are the following:

- Population of individuals is set to 100. This parameter determines the number of individuals (potential solutions) that are maintained and used during the evolution.
- The number of generations in which the genetic algorithm evolves the individuals is established at 50. The evolution is made by applying crossover and mutation operators with some probabilities, and selecting the best individuals of each generation.
- The weights to balance the importance of the population, traffic, and Twitter activity are:  $\omega_P = 0.4$ ,  $\omega_T = 0.3$ , and  $\omega_A = 0.3$ , respectively. These weights are chosen by the user depending on the problem to be optimised. Different values may give better or worse solutions. In this case it has been decided, after a few tests, to give a little more weight to population versus traffic and social networks.

- The cost of each station is  $c_s = \text{€}40000$ , and the cost of a charging pole is  $c_{cp} = \text{€}10000$ .
- The influence radius that each PoI considers about the area that covers (with the intersection of the Voronoi polygon) is set to 300 meters.
- The crossover and mutation probabilities during the evolution are 0.5 and 0.2, respectively. The crossover operator is the graph operator presented in [75] (Section 3.4). The mutation operator is the uniform with a mutation probability of each gene of 0.05.

The rest of the parameters remain with default values since they are out of the scope of these experiments. Additionally, the transformer substations or any forbidden areas have not been considered. For more information about all the genetic algorithm parameters we refer the reader to [116].

### 2.6.1.2 Execution and Results

With all the population, traffic, and Twitter data for Manhattan Island extracted and processed along with the set of PoIs, as well as the other parameters specified in the previous section, we can proceed to run the genetic algorithm. Specifically, we have performed different runs in which we placed 25, 50, 100, and 200 charging stations in Manhattan. The representation of the charging stations that have been placed along with the resulting Voronoi diagram can be seen in Figure 2.9.

In the example with 25 charging stations in Figure 2.9a it can be seen that the charging stations are quite dispersed, although some are more concentrated in the southern area, probably due to the higher activity in the area. However, as there are few stations to be placed there are some areas that are certainly far away from any stations.

The example depicted in Figure 2.9b with 50 charging stations presents a distribution that apparently better covers the island of Manhattan, and especially the southern part, in this case, below Central Park. However, there are still some large areas without adequate charging station coverage.

The example of 100 charging stations in Figure 2.9c already shows a much larger coverage of the entire island of Manhattan, except for the part of central



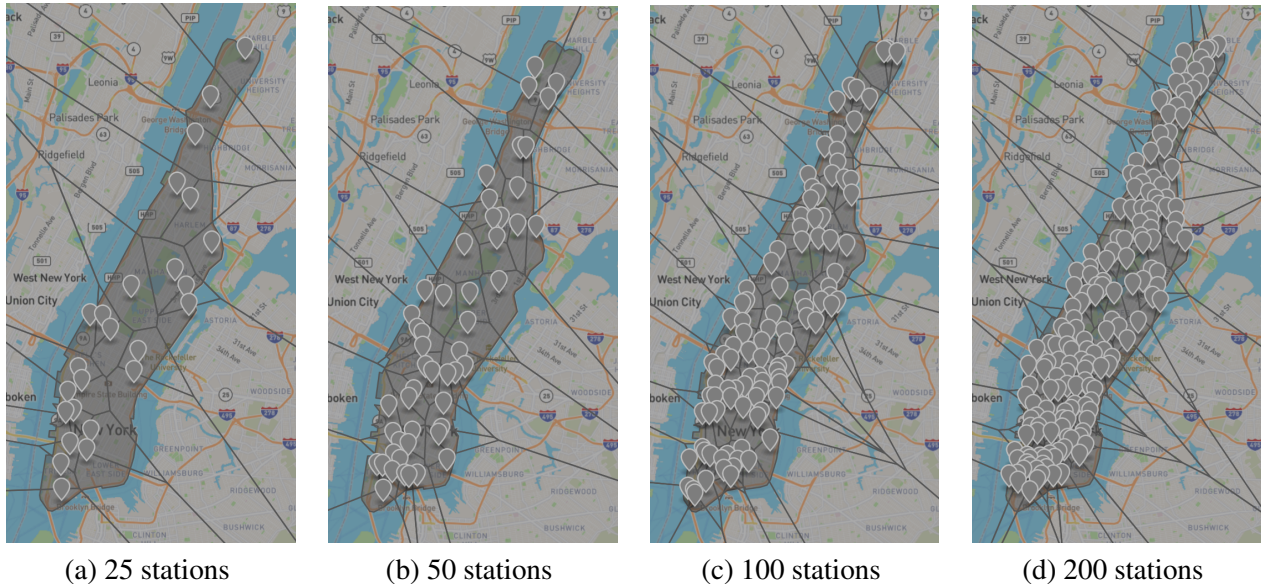


Figure 2.9: Charging stations in Manhattan obtained by the genetic-based generator.

park, where it is not possible to place many charging stations, and also some areas in the north that have fewer stations than in the south, probably due to relatively less activity.

Finally, the example in Figure 2.9d with 200 charging stations already shows a much larger coverage of Manhattan compared to the previous examples. In this case, it becomes more evident that the southern area is fully populated with charging stations, as well as the northern area. In fact, the only gaps that can be seen are in the central park area where it is not possible to place too many stations, and the amount of population and traffic in that particular area is much smaller as it is a significantly large park with no housing or roads.

Table 2.2 shows the monetary cost of each of the Manhattan charging station distributions seen in Figure 2.9. For the cases of 25, 50, and 100 stations, the monetary cost is the result of multiplying the number of stations by 50000€, since in all three cases stations with only one charging point have been placed (the cost of one station has been set at 40000€, and the cost of each charging point at €10000€). For the case of 200 stations, 165 stations are placed, in which several of them have 2-3 charging points. This implies a cost of 40000€ for each of the 165 stations



Table 2.2: Monetary cost of each of the charging station distributions in Manhattan.

stations	cost (€)
25	1,250,000
50	2,500,000
100	5,000,000
200	8,600,000

(without considering the charging points), and then 10000€ for each of the 200 charging points in total. This happens because the genetic algorithm tries to maximise the coverage of the stations to have more utility, so in cases with 100 stations or less, it only places one charging point per station. However, when it can place 200 charging points, it can afford to place more than one charging point per station.

Table 2.3: Utility and cost results for different runs of the genetic algorithm varying the crossover (cxpb) and mutation (mutpb) probabilities for the case with 200 charging points.

cxpb	mutpb	utility	cost (€)
0	0.05	0.03068	9,130,000
0	0.2	0.03195	8,850,000
0	0.5	0.03351	8,650,000
0.25	0	0.03741	8,890,000
0.25	0.05	0.04110	9,410,000
0.25	0.2	0.03978	8,920,000
0.25	0.5	0.04317	8,760,000
0.5	0	0.04156	8,880,000
0.5	0.05	<b>0.04831</b>	<b>8,930,000</b>
0.5	0.2	<b>0.05230</b>	<b>8,600,000</b>
0.5	0.5	0.03923	8,930,000
0.75	0	<b>0.04943</b>	<b>8,970,000</b>
0.75	0.05	0.04263	8,930,000
0.75	0.2	0.04516	8,890,000

Table 2.3 summarises the results obtained concerning the utility and cost of

running the genetic algorithm for 200 charging points in Manhattan. Each row of Table 2.3 corresponds with a pair of crossover and mutation probability values. Note that the sum of both values must not be greater than 1. In addition, results for values  $cspb = 1, mutpb = 0$  and  $cspb = 0, mutpb = 1$  have been excluded since they did not arrive at any feasible solution. The best results are obtained with the crossover probability at  $cspb = 0.5$  and the mutation probability at  $mutpb = 0.2$ . Although also the values  $cspb = 0.5, mutpb = 0.05$  and  $cspb = 0.75, mutpb = 0$  obtain similar results with which there is no significant difference. Thus, we can conclude that any of these 3 combinations of crossover and mutation probability can obtain the best results for the problem we are dealing with.

## 2.6.2 Realistic Route Generation

To illustrate the use of our regression mobility data generator, in this section we describe a complete example in which the TLC Trip Record Data of New York City is used to train a regression model that predicts the taxi demand per taxi zone in a concrete date. The predictions are then used to reproduce the demand on SimFleet's simulations by generating routes for taxi service customers.

### 2.6.2.1 Data Pre-processing

From the many parameters by which a taxi service is characterised, only the service start date and the origin taxi zone ID are kept. Then, the date is split in *month* (1-12), *weekday* (0-6) and *hour* (0-23). The minutes and seconds values of the service start date are discarded so as to group together all services which started during the same hour. Next, the taxi services get grouped by month, weekday, hour and origin taxi zone id and a new column *demand* is created by counting the services being joined together (see Table 2.4). By doing this, the demand value indicates the number of taxi services that started during the indicated month, weekday and hour on the corresponding taxi zone. Dividing the demand value by the total demand (sum of all demand values) we obtain instead an estimation of the percentage of total demand that occurs in each zone.

The process mentioned above can be applied to datasets with services from many months or even many years, as long as they get merged together in the final

Table 2.4: Clean taxi service dataset grouped by month, weekday, hour and origin taxi zone ID. The demand column indicates the number of trips departing from the origin taxi zone at the indicated date and time.

Month	Weekday	Hour	Origin	Demand
1	0	0	4	41
1	0	0	13	59
1	0	0	24	48
...	...	...	...	...
6	6	23	261	18
6	6	23	262	12
6	6	23	263	76

data model. Optionally, it would be possible to create an individual data model for each month with its corresponding regression model. We decided to build a data model with yellow taxi services of the months of January to June of 2019. Also, to restrain the simulation city map to a smaller area, we considered a restricted set of taxi zones inside the Manhattan borough as can be seen in Figure 2.10.

The last step of the pre-processing is to treat the origin taxi zone identifiers as categorical variables, which we do by encoding them into a one-hot encoding (see Table 2.5). The data is then ready to be divided into training and test sets and feed to our regression model.

Table 2.5: Dataset formatted to train a regression model. The origin taxi zone ID values have been converted to one-hot encoding and the demand presented as a percentage of the total demand.

Month	Weekday	Hour	4	13	24	...	261	262	263	Demand
1	0	0	1	0	0	...	0	0	0	1.093e-06
1	0	0	0	1	0	...	0	0	0	1.066e-07
1	0	0	0	0	1	...	0	0	0	1.230e-06
...	...	...	...	...	...	...	...	...	...	...
6	6	23	0	0	0	...	1	0	0	4.798e-07
6	6	23	0	0	0	...	0	1	0	3.198e-07
6	6	23	0	0	0	...	0	0	1	2.026e-06



Figure 2.10: Restricted set of taxi zones of the Manhattan borough.

### 2.6.2.2 Execution and Results

We used an automated Machine Learning process (included in the TPOT tool [113]) to find the most adequate regression model to train with our data. This process automates the pipeline design of machine learning models by performing a search using genetic algorithms to combine and evaluate different models and hyper-parameters.

The pipeline found was composed by a Stacking Estimator with a Decision Tree Regressor followed by a Random Forest Regressor. These models are part of the scikit-learn toolkit [118]. The concrete parameters of each model, also tuned by the automated Machine Learning process, are presented in Table 2.6. This model achieved an accuracy of 0.95 over the test set, which we consider enough given its purpose, which is to generate realistic data.

Once the regression model has been trained, we can generate mobility data as a prediction of taxi demand over the different taxi zones. To do so we first define the simulation time span, the amount of time we want our simulation to model. In the following example, we model a simulation which takes place over a Monday

Table 2.6: Best pipeline found for our dataset.

<b>Decision Tree Regressor</b>	<b>Random Forest Regressor</b>
max_depth = 10	max_features = 0.5
min_samples_leaf = 17	min_samples_leaf = 1
min_samples_split = 7	min_samples_split = 15
	n_estimators = 100
	accuracy = 0.95

(weekday 0) of January (month 1), from 9:00 to 14:00. In addition, we indicate a number of customers per hour, which will inform the simulator about the number of customer agents we want our system to spawn each simulation hour<sup>13</sup>. For our example, we set the number of customers per hour to 1000. Let it be noted that such a number could be indicated for longer time periods like many days or even a whole month; the simulator would then adjust the duration of the simulation accordingly.

With the simulation characterised by the aforementioned parameters, the generator builds the samples to pass to the regression model. As our example takes place in different hours, the model builds, for each hour, samples of services which depart from every taxi zone considered in the simulation. If the simulation was set in different days or months, the generator would create samples in a similar manner to the one described, making sure every possible combination of the parameters is considered.

The samples are passed to the regression model, which outputs a percentage of demand for each one of them. As we mentioned on the data pre-processing (Section 2.6.2.1), our model was trained with data belonging to 6 months. This means the predicted demand is a percentage of the total demand of 6 months. Because of that, we decided to normalise the demand percentage across all samples with the same month, weekday and hour. For our example, that implies normalising the demand across samples with the same hour, which gives us 6 sets of data, each corresponding to an hour (9:00 to 14:00), with normalised demand. Each of the 6 datasets indicates the percentage of demand to be expected in each taxi zone dur-

<sup>13</sup>The real-time duration of an hour of simulation can be adjusted by the user.

ing the same hour. Following, the demand percentage is multiplied by the number of customers per hour (1000), finally obtaining the number of customers that will spawn in each taxi zone during every hour of the simulation. A representation of the dataset for the 9:00 hour can be seen in Table 2.7.

Table 2.7: Data predicted by our regression model. The demand column indicates the percentage of the hourly demand that occurs in a determined taxi zone. The customers column expresses such demand in terms of the number of customers departing from the determined taxi zone.

Month	Weekday	Hour	Origin	Demand	Customers
1	0	9	4	0.002154	2
1	0	9	13	0.013161	13
1	0	9	24	0.003504	3
...	...	...	...	...	...
1	0	9	261	0.003842	3
1	0	9	262	0.023182	23
1	0	9	263	0.026261	26

As it can be inferred, the normalisation of data can be adapted to a concrete simulation setup; i.e., a concrete set of values for the month, weekday, hour and customer amount parameters. If a simulation was defined to take place over many days, and the number of customers was also indicated by day, the demand percentage could be normalised across a day instead of an hour.

As for the last step, the route creation, the generator defines a route for each customer which starts in a random valid location inside its origin taxi zone. The destination taxi zone can be chosen semi-randomly according to the observed taxi services (as commented in Section 2.5.3) or completely random among all considered taxi zones. Once the destination is set, a random valid point inside it is fixed. The origin and destination points are then passed to our routing service and the final route is obtained. During the simulation development, the customer agents will spawn in their origin points. To divide the demand of a single simulation hour into different time intervals the delay parameter (commented in Section 2.5.2) can be used.

## 2.7 Conclusions

This paper has presented a proposal for the generation of more realistic data in agent-based simulation tools related to mobility and transportation. Specifically, the data generation has been focused on the location of EV charging stations and on the generation of routes within the urban environment, but it can be easily adapted to generate other types of infrastructure or data to be required in the urban environment. For the development of the proposal, the simulation tool SimFleet has been used, on which different generators of each kind have been integrated.

We highlight the development of two more complex generators based on artificial intelligence techniques. In the case of the generation of charging stations, a genetic algorithm has been used to optimise the location of stations in the city based on information from open data and other data sources. In the case of route generation, a regression algorithm has been used to generate more realistic routes from historical mobility data. With both generators, the users can simulate different distributions over a city or metropolitan area by recreating mobility, using real data to analyse and compare each distribution. This improves the simulation results facilitating the decision making in municipalities.

Moreover, a case study has also been developed in order to illustrate the use of such generators in common. Specifically, an example has been developed on the island of Manhattan in New York using different sources of real data. Results allow to ensure the usefulness of these generators. As a future work we aim to propose an evolution of the proposed generators for their possible adaptation and integration in other simulation tools similar to SimFleet. The work of adaptation to other tools would mainly consist of transforming the input data generated in our proposal into the appropriate format in each case. As an example, work has begun on developing a data transformation algorithm for the MatSim tool, which requires the input information in xml format divided into different files. On the other hand, we also propose the integration of vehicle reallocation strategies for open fleets in the generators.

# Taxi Services and the Carsharing Alternative: A Case Study of Valencia City

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### Abstract

*The public's awareness of pollution in cities is growing. The decrease of carbon dioxide emissions from the use of fossil-fuel-powered cars stands out among the different viable alternatives. To this purpose, more sustainable options, such as carsharing fleets, could be used to replace private automobiles and other services such as taxis. This type of vehicle, which is usually electric, is becoming more common in cities, providing a green mobility option. In this research, we use multi-agent simulations to examine the efficiency of the current taxi fleet in Valencia. After that, we evaluate various carsharing fleet arrangements. Our findings demonstrate the possibility for a mix of the two types of fleets to meet present demand while also improving the city's sustainability.*



## 3.1 Introduction

In recent years, both city administrators and the general public have become more conscious of the impact of pollution in metropolitan areas. As a result, there are an increasing number of projects aimed at improving sustainability and lowering cities' carbon footprint. Among its crucial targets, the European Union's 2030 climate and energy framework aims to lower the level of greenhouse gas emissions a 40% with respect to 1990<sup>1</sup>. Various municipal councils are advocating for legislation that places considerable limits on polluting automobiles, particularly in urban centres. With this, the inhabitant's quality of life would be generally improved thanks to an enhancement in air quality. Some localities have outright bans on personal petrol-powered vehicles. In contrast, others are more lenient and the worst polluting vehicles (according to their technical datasheet, age or emissions) are the only ones prohibited.

Parallel to this, new mobility service models have emerged that are more suited to users' needs.

Among them, the widely used "ridesourcing service" stands out. This kind of services offer their customers on-demand rides that can be booked though a multitude of platforms (call-centre, mobile application, etc.).

As new mobility options are popularised, the research interest in measuring their urban transportation impact grows too. Authors publish in reference [125] a study centred in San Francisco, California, that compares taxi services against ridesourcing solutions such as the ones offered by Lyft or Uber.

Despite the many similarities ridesourcing and taxi fleets may seem to have, their work reveals the two differ in the amount of satisfied requests and the customer waiting time. Furthermore, around 50% of ridesourcing usage was replacing public transportation and personal vehicle trips, having a deeper effect on urban mobility than if it were just substituting taxi rides.

New means of transportation do not just replace existing modes of transportation; they also produce new transportation trends among consumers. As a result, incorporating electric carsharing fleets [77] into city planning could help to reduce both excess pollution and traffic congestion. Passengers whose journey includes

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<sup>1</sup>2030 climate & energy framework: [https://ec.europa.eu/clima/policies/strategies/2030\\_en](https://ec.europa.eu/clima/policies/strategies/2030_en)

locations which are not served by the city's public transportation options may be able to fulfil their needs with carsharing. Carsharing customers can book a vehicle which is close enough to reach by foot and make a private use of it. At the end of their ride, the vehicle is available for another user. In turn, carsharing could bring a reduction in the amount of active private vehicles in the urban transportation system. The research published in reference [109] reveals a decrease in the average number of vehicles owned per household in Vancouver, Canada, after the implementation of two separate carsharing services. Moreover, many users may no longer need to possess a vehicle in the future, which will substantially influence sustainability on multiple levels, including direct emissions from the active automobiles as well as indirect contaminating procedures for vehicle manufacturing.

In contrast with the stated above, authors in reference [79] declare their data shows no significant relation between car ownership and free-floating car-sharing in Germany. This goes to show the complexity of urban mobility and how its is also affected by sociological factors. Nevertheless, the aforementioned study does not analyse impact on urban rides. Many taxi consumers would be eager to use carsharing services because they may be more cost-effective if the service is competitively priced. However, carsharing vehicles cannot meet all taxi demand. Some people are unable to drive or have special needs that this type of fleet can not meet. A taxi-like service will never be completely substituted.

Taxi and dial-a-ride fleets, among other conventional urban transportation services, may be partially substituted by carsharing services with potentially lower environmental impact. The carbon dioxide emissions of carsharing are reduced thanks to the nonexistence of empty movement (vehicle displacement without passenger) [48]. Furthermore, as hybrid and fully electric vehicles perform well in metropolitan settings, they may easily implement carsharing fleets. As a result, even if carsharing serves a small portion of the city's taxi demand, it will result in a cleaner environment. With this focus, a Beijing-centred work [36] investigates the features a carsharing fleet needs to outperform the existing taxi service with regard to travelling costs. A similar research [165], also set in Beijing, assesses the efficiency of different arrangements carsharing services by means of simulation.

As can be inferred from above, many studies that look at the efficiency of urban transportation alternatives focus on a specific town or urban area. This is a sensible choice because a critical aspect of an excellent urban fleet performance is its ability

to adapt to citizens' mobility patterns and travel preferences. We pursue such a mindset by centring our research in the urban area of Valencia, Spain.

Valencia's government has been particularly engaged in developing the sustainable development goals (SDG) of the United Nations for the past few years. Among them, SDG 11: *Sustainable Cities and Communities* is specially relevant to our work. Authorities are implementing it through many policies such as the prohibition of petrol-powered vehicles in specific sections of the urban centre, pedestrianising roads and squares, developing additional parks and green spaces, and finally encouraging electric-powered vehicle usage.

Valencia had never had a carsharing service previously, and it was only recently that a small company named *Cargreen*<sup>2</sup> began offering it on May 9, 2021, with a fleet of 100 electric cars. The absence of this service means, in turn, the absence of GPS data belonging to carsharing trips. Nonetheless, we have data on the population, transportation, and social media activity that we utilise to recreate Valencian inhabitants' mobility patterns.

The findings of several of the research mentioned above are based on surveys and fleet data analysis. Instead, we employ agent-based modelling to simulate various mobility systems and their users, being able to define behaviours for each of them. In addition, our experimental setup allows us to simulate vehicle fleets directly in the city of Valencia. The multi-agent simulator SimFleet [117] is employed to run different scenarios and gather data that is later analysed to draw conclusions. The research questions of this article are first to assess Valencia's public taxi service efficiency from two viewpoints: sustainability, with focus on carbon dioxide emissions, and quality of service, mainly indicated by customer satisfaction. Then, we want to present the characteristics of a free-floating car-sharing service so that is able to absorb a portion of the mobility demand in a sustainable manner while being a competitive alternative. Our results, supported by the experimental simulations, show there is potential to reduce part of the public taxi fleet in favour of a carsharing fleet. With both alternatives working together to serve the displacement demand, we could preserve a reasonable degree of customer satisfaction while improving the general sustainability of the urban mobility system. The present work is an extension of reference [94].

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<sup>2</sup><http://cargreen.es/>

The rest of the paper is structured as follows. Section 3.2 introduces the software and the data employed to build the simulation scenarios, as well as the system modelling and the experimental setup of this work. Then, Section 3.3 details the development of the various experiments, the metrics that evaluate fleet performance, and the collected results. Section 3.4 presents a general discussion on the results and findings of this work. Finally, in Section 3.5 we present our conclusions and future work.

## **3.2 Materials and Methods**

This section describes the software that was employed to build realistic simulation scenarios and the data used to this end. In addition, the simulator and its key features are introduced. Finally, the system modelling and our experimental setup are briefly described.

### **3.2.1 Simulation Environment: SimFleet**

SimFleet [117] is a multi-agent based urban fleet simulator, initially intended for an easy implementation and experimentation of agent strategic behaviours. In this work, we carry out simulations with a modified SimFleet version. We the authors of the current work have actively contributed to SimFleet's development, which allows us to easily modify its operation to adjust the simulations to our research. It is implemented with SPADE [53], a Python agent development environment. This feature enables us to introduce to the simulations agents with behaviours and strategies defined by ourselves. In addition, SPADE provides scalability and more tools to develop complex mechanisms of communication among agents. For the current research, we have defined protocols for operating a taxi and a carsharing fleet. Moreover, we implemented separated customer strategies to make use of those services and a third one which enabled customers to use both. This was possible thanks to our experience with SimFleet and our access to its code on a lower level, which allowed us to alter its functionalities.

The urban mobility simulations are developed in SimFleet with three types of agents: FleetManager, Transport and Customer agents. Each fleet has a FleetMan-

ager, which generally acts as an intermediary between the users of such a fleet and its vehicles. In turn, each vehicle is represented by a Transport agent. Finally, Customer agents portray the actors that use the transportation system. We simulate three different transportation scenarios for this work: a taxi fleet, a car-sharing fleet, and finally, a setting where both fleets operate over the same urban area. The specific behaviours and strategies of the three types of agents will vary for each scenario. However, the simulation goal is constant: all customers of the transportation service must get to their destination. Following, we briefly describe the particularities of the agent modelling of each fleet.

In taxi simulations, the FleetManager acts as a centralised entity that selects the taxi to which a particular customer request is sent. The followed strategy is to forward the request to the nearest available taxi. Transport agents act as a taxi, picking the customers up at their origin location and dropping them off at their destination. Lastly, Customer agents create a displacement request (from their current position to their destination) and send it to the FleetManager. Once they get assigned a vehicle, they wait for it to arrive.

To simulate carsharing fleets, in contrast, we employ an enhanced version of SimFleet, described in reference [97]. Such a version allows the three aforementioned agent types to simulate a *free-floating carsharing fleet*, implementing new behaviours for all of them.

The FleetManager now has to notify clients of any available (non-booked) car and its location. Transports play a more passive role, remaining parked at their origin locations and waiting for a booking request. On the other hand, customer agents can now choose the car they want to book based on their requirements. Furthermore, they must walk to their reserved vehicle to use it. A user-defined parameter limits the distance they can walk. Once in their transport location, they drive to their destination and finally park the car, leaving it available again. Ultimately, in scenarios where both fleets are present, the crucial difference appears in the Customer agent behaviour. The FleetManager and Transport agents of each fleet behave according to their fleet type (carsharing or taxi), as explained above. Regarding customers, these simulations accept taxi and carsharing customers and a new so-called hybrid customer. Hybrid customers will initially aim to book a carsharing vehicle. If unable, they will instead call for a taxi. Their behaviour, therefore, begins as a carsharing customer and transitions to a taxi customer if

necessary to reach their destination.

### 3.2.2 Data Generation

A simulation can recreate reality if the data on which it is based are accurate. Therefore, we decided to base our simulations on real data from Valencia, Spain, the location of our research. The regional<sup>3</sup> and national<sup>4</sup> governments maintain open databases through which we have access to geolocated data: amount of inhabitants per area, average traffic intensity on each city road, and the positions of taxi stops, among others. Such data is fed to the *Load Generators*, presented in reference [99].

These generators are used to allocate the elements of a simulation (customers, vehicles, resources, etc.) in the scenario in a way that reproduces the real city-data. Before the start of the allocation, the simulated area is split into multiple subareas. The *granularity* parameter determines the number of subareas. Then it computes a probability distribution for the entire area, attributing a selection probability to each subarea. This probability is calculated based on the population, traffic, and social activity in the subarea. The different factors are joined by Eq (3.1), where  $O_i$  indicates a subarea,  $p_i, t_i$ , and  $a_i$  the amounts of population, traffic, and social activity within  $O_i$ , respectively; and  $w_p, w_t$  and  $w_a$  are weights that regulate the influence of each type of data over the final probability value. The amount of data in a subarea is divided by the number of occurrences of the same type of data ( $P, T$ , and  $A$ , respectively) in the entire region.

(3.1)

$$\text{prob}(O_i) = w_p \cdot \frac{p_i}{\sum_{j=1}^P p_j} + w_t \cdot \frac{t_i}{\sum_{j=1}^T t_j} + w_a \cdot \frac{a_i}{\sum_{j=1}^A a_j}; \text{ with } w_p + w_t + w_a = 1$$

For this work, the probabilistic map obtained by the *Load Generators* has been enhanced considering the main type of activity developed in each area of the city of Valencia. According to this, we find residential, primary, secondary and service industries, hospitals, and green areas, among others. By blending city and area

<sup>3</sup>*Govern Obert*. [www.valencia.es/val/ajuntament/govern-obert](http://www.valencia.es/val/ajuntament/govern-obert)

<sup>4</sup>*Instituto Nacional de Estadística* (INE). [www.ine.es/index.htm](http://www.ine.es/index.htm)

data, we better characterise the movement patterns of citizens. Although we do not have data on specific GPS routes, we can define an origin-destination matrix. The paths of the agents are constructed as follows: Agents are assigned an origin point (contained in one of the sub-areas) in a semi-random way, according to the probabilities. Varying the values of the weights ( $w_p$ ,  $w_t$ ,  $w_a$ ), we can increase the importance of the different factors, which is helpful to introduce different types of agents. For instance, in creating customer agents, more weight is given to population and social activity with respect to traffic. As for the destination of the journey, once the origin point has been selected, the map probabilities are recalculated, taking into account the activity type of each sub-area. For example, a journey departing from a residential area may be more likely to finish in an industrial sector and vice versa.

With our generators, we introduce individual citizens (customer agents) with their own displacement needs. Such needs can be satisfied with one of two options: taxi or carsharing services. The demand generation is transparent to the differences among concrete customer agents. Displacement requests are created as one-shot trips similar to those a taxi customer would demand. This trip model also fits the concrete type of carsharing mobility we study: free-floating carsharing, where, in general, once the customer reaches a destination, the vehicle will be available for any other user. With the described data generation setting, we improve the quality of our simulations with respect to those obtained with random agent movement.

### 3.2.3 System Modelling

The simulations are performed in the city of Valencia, Spain. The data generators (Section 3.2.2) make use of geolocalised population, traffic and Twitter activity data to fill the scene with transport and customer agents, assigning realistic routes to the latter.

The scenario is loaded by SimFleet (Section 3.2.1) and the simulation executed. The system keeps track of different metrics regarding elapsed times and travelled distances throughout the simulation. These values will be collected once the simulation finishes to assess the performance. Following, we briefly describe the flow of each type of simulation.

In taxi simulations the fleet vehicles are allocated in various points within the city. Customers send travel requests to the fleet manager upon spawning. The fleet manager forwards each request to the closest available taxi to the customer. The taxi accepts the request, moves to the customer's position, picks them up and drives to their destination. Once at their destination, the customer agent completes its execution, and the taxi informs the fleet manager of its availability. When the fleet gets saturated and there are no free taxis, the customer waits a fixed amount of time before sends their request again. A customer can wait for a taxi as much as its maximum waiting time allows them. Once that time elapsed, if the customer could not get a taxi assigned, it will be marked as "unsatisfied" and leave the simulation.

Regarding carsharing simulations, the fleet vehicles are also allocated in various points within the city. Upon spawning, customer agents ask the fleet manager for the location of available vehicles. The customer can book a vehicle among those that are within its maximum walking distance. In general, it will aim to book the closest one to them. When the customer receives the booking confirmation it starts walking towards their vehicle. Once at the vehicle's location, the customer unlocks it and drives to their destination. Finally, the customer completes its execution and the vehicle informs the fleet manager of its new location and availability. If the customer is unable to book a transport after its maximum waiting time has expired it will be marked as "unsatisfied" and leave the simulation. This generally occurs when the customer does not have an available vehicle within walking distance at any point in time.

Finally, for hybrid simulations, those with both types of fleet, we have defined three types of customers: taxi, carsharing and hybrid customers. On the one hand, taxi customers can only travel by calling for a vehicle to the taxi fleet. Whether it is due to a lack of driving licence, a desire to avoid parking or simply not wanting to drive in the city centre, there will always be users who prefer a taxi service to one such as carsharing. On the other hand, carsharing customers will only use a carsharing vehicle. For these customers, we assume that they either prefer the lower price offered by the use of carsharing vehicles or that they have a strong environmental conscience, which pushes them to use more environmentally-friendly vehicles. Finally, hybrid customers have a utilitarian approach. They will first try to book a carsharing vehicle, knowing its use is cheaper and less polluting than a taxi ride. However, if they cannot book a vehicle after its maximum waiting time



has elapsed, they will instead call for a taxi, as reaching their destination is what drives them the most. Because of that, the satisfaction dynamics are changed in hybrid-type customers: if a hybrid customer is unsatisfied, it means they have tried to book a carsharing vehicle for its maximum waiting time and failed and later tried to call a taxi and received no answer for another maximum waiting time. The other two types of customers preserve the original behaviour described above.

All types of simulation will stop once every customer is either at their destination or unsatisfied.

### 3.2.4 Experimental Setup

Following, we present the system metrics and the simulations used to analyse Valencia's taxi and carsharing fleets. The experimentation consists on 15-hour simulations of transportation activity in the city with a variable demand generation that is higher at peak hours.

We defined metrics for customers' time and fleet vehicle distances and assignments, which are analysed to assess the performance of a fleet. Most metrics evaluate both carsharing and taxi fleets, although some are only meant for a concrete type or customers. All metrics are listed in Table 3.1.

The performance of a fleet is evaluated from two different angles. On the one hand, from the customer viewpoint, lower waiting times and shorter walked distances boost satisfaction. On the other, when it comes to the fleet's economic efficiency and environmental sustainability, shorter empty distances and a higher number of assignments and occupied distances are good indicators. Finally, the universal simulation metrics are useful to measure the effect different number of vehicles and/or costumers has in various scenarios.

The city of Valencia has a total of 2841 registered taxis<sup>5</sup>, but not all of them are active simultaneously. A maximum of 1044 taxis can be in service together, although the concrete number is highly variable according to weekday and time of the day. During concrete low demand periods, the city has had less than 200 active taxis. Regrettably, because of the absence of official data on the number of active taxis each hour, we decided to portray it as a percentage of the overall number of taxis. Our baseline simulation experiment presents a taxi fleet of 840 vehicles, an

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<sup>5</sup>Spanish National Statistics Institute <https://www.ine.es/jaxi/Datos.htm?tpx=32954>

Table 3.1: Description of the output metrics of the simulation. Customer and transport metrics describe individual factors relevant only to those types of agents. The overall simulation metrics provide indicators to estimate service quality and fleet performance.

<b>Customer metrics</b>	
Walked distance	Distance walked by the customer to its booked transport's location
Waiting time for a booking	Time a customer waited to get a confirmed booking
Waiting time for a pick up	Time a customer waited for a taxi to pick it up
Satisfaction	Boolean that indicates whether a customer has reached its destination
<b>Transport metrics</b>	
Assignments	Total number of served passengers
Empty distance	Distance travelled by a taxi without a passenger
Customer distance	Distance travelled by a vehicle while carrying a passenger
<b>Simulation metrics</b>	
Avg. customer booking time	Average of satisfied customers' waiting for booking times
Avg. customer waiting time	Average of satisfied customers' waiting for pick up times
Avg. customer walked dist.	Average of satisfied customers' walked distances
Satisfaction %	Percentage of satisfied customers (out of the total number of customers)
Total assignments	Number of assignments of a whole transport fleet
Avg. assignments	Average number of assignments per fleet vehicle
Avg. empty distance	Average empty distance travelled by the fleet vehicles
Avg. distance	Average distance travelled by the fleet vehicles
Unused vehicles	Number of vehicles with 0 assignments
CO <sub>2</sub> emissions	Approximated amount of carbon dioxide emitted by the fleet

80% of the maximum number of active taxis. We hope that by doing so, we will be able to compensate for periods when taxi amounts are greater or lower.

Regarding the demand modelling, we defined individual customers with a spawning time, location, and destination at least 2 km away from their origin. Our simulations reproduce 15 city activity hours, between 7:00 (AM) and 22:00 (10:00 PM). We have assigned to each one-hour interval a concrete demand intensity. Such intensity is related to the number of customers spawning within the hour. Specifically, we defined four intensities: Low, with 250 customers; Medium-Low, with 500 customers; Medium-High, with 750 customers; and High, with 1000 customers. We divided a total of 10,000 customers into one-hour intervals as shown in Table 3.2. The intervals between 9:00 and 10:00, 14:00 and 15:00, and 18:00 and 19:00 have been assigned a high demand. This reflects commuting to and from

Table 3.2: Mobility demand in terms of the number of customers per simulation hour.

Simulation hour	Customers	Demand intensity
7:00 – 8:00	500	Medium-Low
8:00 – 9:00	750	Medium-High
9:00 – 10:00	1000	High
10:00 – 11:00	750	Medium-High
11:00 – 12:00	250	Low
12:00 – 13:00	500	Medium-Low
13:00 – 14:00	750	Medium-High
14:00 – 15:00	1000	High
15:00 – 16:00	750	Medium-High
16:00 – 17:00	500	Medium-Low
17:00 – 18:00	750	Medium-High
18:00 – 19:00	1000	High
19:00 – 20:00	750	Medium-High
20:00 – 21:00	500	Medium-Low
21:00 – 22:00	250	Low
Total	10,000	

work and taking children to and from school or home.

The results of the baseline taxi simulation are compared with various configurations of carsharing fleets, aiming to assess their performance. In order to do so, another five simulation scenarios have been developed. The demand modelling described above was preserved, but the transportation service was implemented by means of a carsharing fleet. Each scenario has its own number of vehicles: *Cs-1000*, *Cs-840*, *Cs-560*, *Cs-280*, and *Cs-140*, which present fleets of 1000, 840, 560, 280 and 140 carsharing vehicles, respectively.

We can estimate how much different carsharing fleet designs can cover mobility demand by measuring the percentage of satisfied users. Furthermore, we may compare each fleet's greenhouse gas emissions as a function of the distance travelled by their vehicles.

The movement speed for vehicles is set to 40 km/h whereas for pedestrians

(carsharing users) is of 4 km/h. With this, we average between the urban road speed limit of 50 km/h and the residential area speed limit of 30 km/h, as well as the time spent waiting in traffic lights. Regarding pedestrians, the average human walking speed of 5 km/h has been reduced by 1 to palliate our simulator's absence of traffic lights and the extra time they would incur. The maximum waiting time of all customers is set to 12 minutes (720 seconds). In addition, carsharing users can only book a vehicle which is within a 1000 meters walking distance. As a result, if a customer is unable to book a vehicle or has not been picked up by a taxi after 12 minutes elapse, it will be marked as unsatisfied and leave the simulation.

## **3.3 Results**

This section presents the experiments carried out with the different types of fleet. First, the results for different carsharing fleet sizes to cover the demand in Valencia are shown. Then, we present the results for covering the same demand with different taxi fleet sizes. Finally, the results with combined hybrid fleets, i.e., a carsharing fleet and a taxi fleet, to cover the demand in the city are shown.

### **3.3.1 Carsharing Fleet Performance**

In the first experiment, presented in Table 3.3, the performance of the carsharing fleet configurations is compared against the baseline configuration (Taxi-840). Time values in the table should be regarded as a guideline rather than an exact time measurement, as factors such as traffic congestion and traffic lights are not taken into account. In the taxi simulation, the customer booking time (Table 3.3, first row) shows the time required to call the taxi service provider and ask for a ride. The customer waiting time, on the other hand, indicates the average time elapsed between the call and the client pickup. These definitions vary for carsharing customers, for whom the booking time display the time spent on the app looking or waiting for an available vehicle to book. Therefore, the waiting time reflects the time it took the used to walk to the vehicle. All other metrics are common for the two types of services (please refer to Table 3.1 for a detailed explanation of each metric).

Table 3.3: Simulation metrics comparison of the carsharing configurations (labelled as “Cs-” followed by the number of vehicles in their fleet) with the baseline taxi configuration of 840 transports.

	Taxi-840	Cs-1000	Cs-840	Cs-560	Cs-280	Cs-140
Avg. cust. booking time (min)	1	2.3	1.9	1.2	1	3
Avg. cust. waiting time (min)	2.5	7.6	7.1	7.2	8.3	11.6
Avg. cust. walked dist. (m)	0	518	522	554	611	655
Satisfaction %	99.87	90.77	89.57	82.86	61.59	38.21
Total assignments	9987	9077	8957	8286	6159	3821
Avg. assignments	12.85	9.57	10.95	14.85	22.15	27.49
Avg. dist. per assignment (Km)	6.13	5.44	5.47	5.47	5.43	5.41
Unused vehicles	34	52	22	2	2	1
Total empty distance (Km)	7423	0	0	0	0	0
Total distance (Km)	60,909	48,821	48,299	44,763	33,246	20,593
CO <sub>2</sub> emissions (tonnes)						
Gasoline	6.68	5.35	5.30	4.91	3.65	2.26
Diesel	7.65	6.13	6.07	5.62	4.18	2.59

As can be seen, the fleet of 840 taxis achieves a high percentage of customer satisfaction. Its average booking and waiting times indicate that the fleet operated smoothly over most of the 15 hours. However, it got overloaded at some point, as 13 customers could not be served before their maximum waiting time elapsed. Each taxi made an average of 12.85 trips, an average of 6.13 Km long (including customer pickup). Still, 34 taxis were never given assigned to a customer. This is probably due to their original spawning location, making them unfit to serve any trip.

Before comparing the performance of the different carsharing fleets with the baseline, it is interesting to visualise how the demand evolved throughout the simulation. Figure 3.1 shows the evolution of the number of waiting and unsatisfied customers during the 15-hour period of the simulation. The number of waiting customers is indicated in the left vertical axis and represented by areas with a different shade of blue for each fleet configuration. Such a value is increased each time a customer enters the simulation. On the other hand, it decreases when a customer has booked a vehicle or its state changes to unsatisfied. The number of unsatisfied customers is indicated in the right vertical axis and represented by lines with dif-

ferent colours and patterns for each fleet configuration. This value is initially 0. As the simulation is carried out, the number increases each time a customer exceeds its maximum waiting time and is therefore marked as unsatisfied.

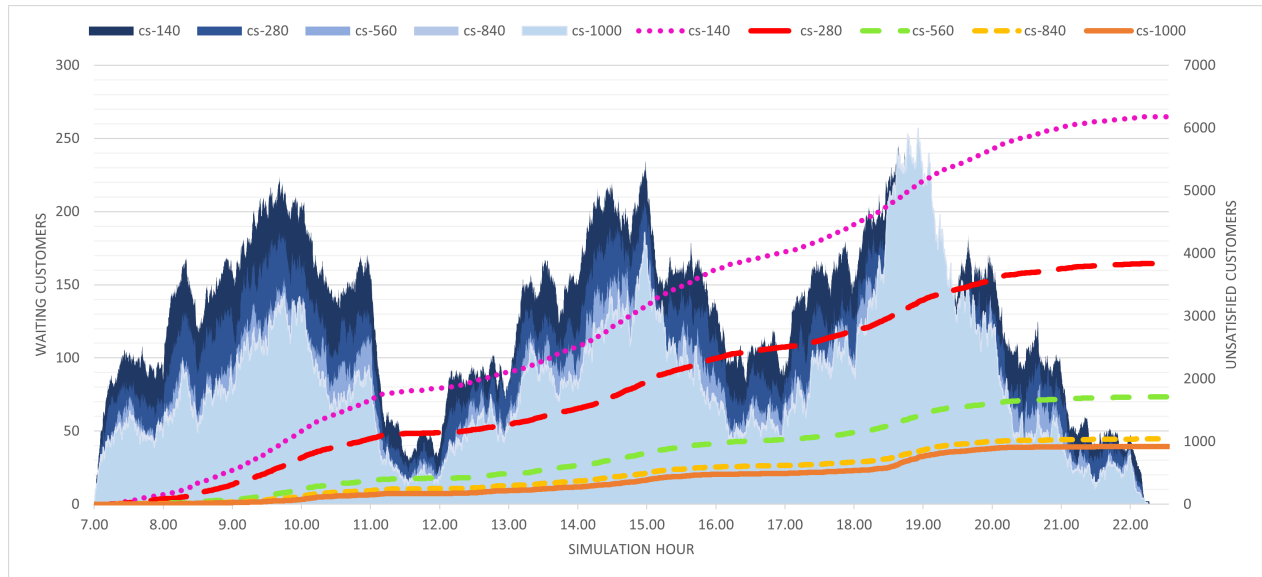


Figure 3.1: Visualisation of the evolution of the amounts of waiting clients (left vertical axis) and unsatisfied clients (right vertical axis) in the different carsharing simulations according to the simulation time (in hours). Simulations are labelled with “cs-” followed by the number of vehicles in their fleet.

Observing the shape of the areas of Figure 3.1 change along the horizontal axis, we can visualise the demand peaks shown in Table 3.2. The amounts of waiting customers reach their maximum values between the 9:00–10:00, 14:00–15:00 and 18:00–20:00 time periods, reaching their absolute maximum in the evening for all configurations. Configurations cs-1000 and cs-840 behave similarly in terms of waiting and unsatisfied customers. This is clear as their areas and lines are almost overlapped, having cs-840 a slightly worse performance (higher values). The performance worsens as the fleet vehicles are reduced, as may be expected. The difference between unsatisfied customers of the cs-560 and cs-280 configurations is notable, as the latter significantly worsens the metric. The same can be observed for configuration cs-140.

Going back to Table 3.3, configuration taxi-840 outperforms all carsharing configurations in terms of customer satisfaction. The carsharing fleet cannot absorb

the mobility demand with the restrictions we have introduced. However, we recognise that comparing taxi and carsharing fleets directly is not fair since they are so dissimilar. Taxis are most commonly utilised for brief, one-time trips. Carsharing services, on the other hand, may be used for a similar purpose or to replace private vehicles and even public transportation. Moreover, carsharing users must be willing to drive and park the transport on their own. Nonetheless, the findings suggest that a carsharing fleet may serve a portion of the taxi market (38.21% of customers with a carsharing fleet of only 140 vehicles, 61.59% with a fleet of 280 vehicles, and up to 82.86% with 560 vehicles), decreasing emissions by reducing the number of vehicles and the distance travelled.

From the standpoint of sustainability, it is noteworthy to observe how the average number of assignments per vehicle improves as the number of vacant vehicles decreases. Fewer transports have a lower environmental impact, both in terms of vehicle production and subsequent maintenance. Furthermore, it indicates a lower chance of traffic congestion, which reduces pollution and enhances the overall quality of life for all participants of the urban transportation system.

The use of carsharing vehicles has a simple but powerful benefit: it prevents empty vehicle movement. This is because our modelling disregards the relocation of vehicles, as this is a very complex problem which needs its own separate research, and thus is outside the scope of the current work. Table 3.3 presents carbon dioxide emissions for the different fleets assuming an average city consumption of 5 L/100km<sup>6</sup> and presenting two values according to the type of fuel (diesel or gasoline). The results indicate that around 7423 km could be saved each 15 hours by avoiding empty journeys (with a fleet of 840 taxis). This represents a saving of around 0.81 to 0.93 tonnes of CO<sub>2</sub><sup>7</sup>. Comparing simulations Taxi-840 and Cs-840, the reduction may reach around 1.38 to 1.58 tonnes. The savings would be significantly higher if the carsharing fleet was made up entirely of completely electric vehicles. The fleet in *Cs-140*, for example, covers 20,953 km every 15 hours. Travelling such a distance in a car with the mentioned consumption would result in around 2.26 to 2.59 tonnes of CO<sub>2</sub> emissions. All travelling emissions could be prevented if every car was electric.

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<sup>6</sup>Value obtained as an average of the gas consumption of vehicle models generally used for taxis in Valencia.

<sup>7</sup>Computation made with <https://calculator.carbonfootprint.com/calculator.aspx?tab=4>

### 3.3.2 Taxi Fleet Reduction

A different approach to increasing the sustainability of a transportation system is to reduce the number of vehicles in it. This rather drastic change must be carefully addressed to preserve an adequate level of service quality. In the following experimentation, we carried out various taxi fleet simulations, reducing the number of taxis in each fleet.

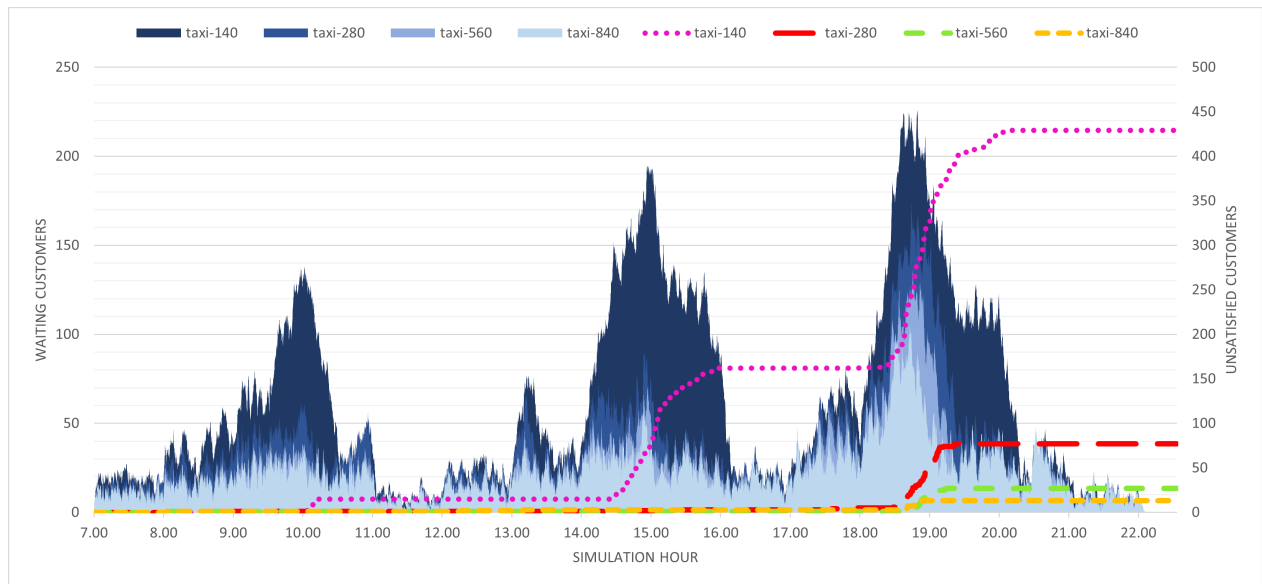


Figure 3.2: Visualisation of the evolution of the amounts of waiting clients (left vertical axis) and unsatisfied clients (right vertical axis) in the different taxi simulations according to the simulation time (in hours). Simulations are labelled with “taxi-” followed by the number of vehicles in their fleet.

Figure 3.2 shows the evolution of the number of waiting and unsatisfied customers throughout the different simulations. This graph follows the format of Figure 3.1. Please refer to Section 3.3.1 for a detailed explanation of the graph. As it can be seen, the number of waiting customers reflects the three high-demand periods. In this case, configuration taxi-140 has a significantly higher number of waiting customers than the other configurations. Regarding the number of unsatisfied customers, the fleets of configurations taxi-280, taxi-560 and the baseline taxi-840 only get overloaded during the third high-demand period (18:00–20:00). In con-



figuration taxi-140, however, the fleet gets overloaded during each high-demand period, increasing its number of unsatisfied clients each time.

Table 3.4: Comparison of global simulation metrics of the different taxi fleets (labelled as “Taxi-” followed by the number of vehicles they contain) against the baseline taxi fleet of 840 vehicles.

	Taxi-840	Taxi-560	Taxi-280	Taxi-140
Avg. cust. booking time (min)	1	1	1	1
Avg. cust. waiting time (min)	2.5	2.8	3.5	6
Avg. cust. walked dist.	0	0	0	0
Satisfaction %	99.87	99.73	99.23	95.71
Total assignments	9987	9973	9923	9571
Avg. assignments	12.85	18.15	35.8	68.4
Avg. dist. per assignment (Km)	6.1	6.3	6.6	7.7
Unused vehicles	34	5	0	0
Total empty distance (Km)	7423	9154	12,331	21,972
Total distance (Km)	60,909	62,571	65,487	73,253
CO <sub>2</sub> emissions (tonnes)				
Gasoline	6.68	6.86	7.18	8.03
Diesel	7.65	7.86	8.23	9.20

The simulation metrics of the different fleets, presented in Table 3.4, show good satisfaction percentages. It is especially remarkable the fleet’s operation in taxi-140, which only reduces satisfaction by a 4.07%, while its vehicles have been reduced an 83.33% with respect to the baseline.

Any conclusions drawn from our experimentation must be understood in the context of our simulation settings. Nevertheless, we see a potential for a reduction of Valencia’s taxi fleet (or the optimisation of its operation), aiming to lower its environmental impact. In this regard, we can see how the travelled distances, as well as the carbon dioxide emissions, increase as we reduce the number of vehicles. This is because the less taxis a fleet has, the more distance does each individual vehicle cover. Therefore, to correctly assess the sustainability in this case, we would need to compare the impact of producing and maintaining a vehicle against the impact of its usage emissions.

### 3.3.3 Hybrid Mobility Approach

The last set of simulations we performed present a hybrid approach to urban mobility. In our previous experimentation, the taxi fleet shows consistently better customer satisfaction. In contrast, the carsharing fleet presents the advantage of reducing the distances travelled by vehicle and consequently carbon dioxide emissions. This is, as mentioned before, because in carsharing the customer pickup is avoided. In turn, many clients may find themselves without a vehicle to book, as all of them parked are too far away. We combine a taxi and a carsharing fleet in the simulation scenario, aiming to balance both metrics.

We created five new simulation scenarios. The distribution of customers by type in these simulations is 70% hybrid customers, 20% taxi customers and 10% carsharing customers (see Section 3.2.3 for a description of each customer type). The different instances vary in the number of vehicles for each fleet. Simulation (*cs-280, taxi-280*) has the highest number of transports, with a fleet of 280 carsharing vehicles and another with 280 taxis. Analogously, we defined simulations (*cs-280, taxi-140*), (*cs-140, taxi-140*), (*cs-140, taxi-70*), and (*cs-70, taxi-70*). As it can be seen, we intend to study the reduction of the number of vehicles, prioritising the taxi fleet.

The results of the simulations are collected in Table 3.5. We must take into account certain factors to analyse them. As hybrid customers can be served by the carsharing and the taxi fleets, some of their metrics are presented split by fleet type. In addition, the percentages of unsatisfied customers of a particular type are calculated over the total number of customers of that type (7000 hybrid, 2000 taxi, 1000 carsharing). Finally, please note that the increase in the customer waiting time for a taxi vehicle is partially due to the behaviour of hybrid customers, which exhaust their maximum waiting time (12 minutes) trying to book a carsharing vehicle before calling a taxi.

The results show that global customer satisfaction is relatively acceptable for every fleet combination tested. As expected, reducing the number of vehicles reduces the quality of service. Nevertheless, even with the smallest fleets (70 carsharing vehicles and 70 taxis), 74.06% of customers are satisfied. Among customers of different types, we can see how hybrid customers benefit from their freedom of choice, as they show lower dissatisfaction percentages for every simulation. In

Table 3.5: Simulation metrics comparison of the hybrid simulations (labelled as “cs-” followed by the number of vehicles in the carsharing fleet and “taxi-” followed by the number of vehicles in the taxi fleet).

	Simulation					
	cs-280 taxi-280	taxi-140	cs-280 taxi-140	cs-140 taxi-70	cs-140 taxi-70	cs-70 taxi-70
<b>Customer metrics</b>						
Avg. taxi cust. waiting time (min)	11		11.4	12.8	15.1	16.2
Avg. cs cust. waiting time (min)	8.9		9.2	11	11	12.3
Avg. hybrid cust. waiting taxi (min)	17.2		17.4	17.1	19.7	19.8
Avg. hybrid cust. waiting cs (min)	8.9		9.2	11.1	11	12.3
Global satisfaction %	91.58		91.88	89.62	83.48	74.06
Hybrid cust. travelled by taxi %	31.11		31.34	53.91	45.34	55.69
Hybrid cust. travelled by cs %	64.46		64.35	41.83	43.71	24.46
Unsatisfied taxi customers %	8.70		7.70	7.00	16.20	22.60
Unsatisfied cs customers %	35.80		36.40	60.00	56.20	75.20
Unsatisfied hybrid customers %	4.43		4.20	4.26	10.94	19.86
<b>Transport fleet metrics</b>						
Total assignments	9158		9188	8962	8348	7406
Taxi fleet assignments	4043		4040	5641	4850	5446
Cs fleet assignments	5115		5148	3321	3498	1960
Avg. assignments (taxi)	14.43		28.86	40.29	69.29	77.80
Avg. assignments (cs)	18.27		18.37	23.72	24.99	28.00
Avg. dist. per assignment (taxi) (Km)	6.4		6.8	6.9	8.5	8.73
Avg. dist. per assignment (cs) (Km)	5.4		5.4	5.4	5.4	5.4
Unused vehicles (taxi)	21		2	0	0	0
Unused vehicles (cs)	3		4	1	1	1
Total empty distance (taxi) (Km)	4584		6712	8878	15132	18454
Total empty distance (cs) (Km)	0		0	0	0	0
Total distance (taxi) (Km)	26,106		27,742	39,122	40,964	47,570
Total distance (cs) (Km)	27,850		27,842	17,956	18,957	10,548
<b>Carbon dioxide emissions</b>						
CO <sub>2</sub> emissions (taxi) (tonnes)						
Gasoline	2.86		3.04	4.29	4.49	5.22
Diesel	3.28		3.48	4.91	5.15	5.98
CO <sub>2</sub> emissions (cs) (tonnes)						
Gasoline	3.05		3.05	1.97	2.08	1.16
Diesel	3.50		3.50	2.26	2.38	1.33
Avg. fleet CO <sub>2</sub> emissions (tonnes)	6.35		6.54	6.73	7.05	6.84

this regard, carsharing customers are more penalised, as they have more restrictions when it comes to booking a vehicle (maximum walking distance and the common maximum waiting time). Finally, it is interesting to see the evolution of the percentage of hybrid customers served by each type of fleet. In simulations (*cs-280, taxi-280*) and (*cs-280, taxi-140*) most of the hybrid customers are able to book a carsharing vehicle. However, when that fleet is reduced to 140 vehicles, the greatest part of hybrid customer demand is absorbed by the taxi fleet, as (*cs-140, taxi-140*) and (*cs-70, taxi-70*) show. Lastly, configuration (*cs-140, taxi-70*) presents a certain balance in this aspect.

Analysing the travelled distances of each fleet, we see that both (*cs-280, taxi-280*) and (*cs-280, taxi-140*) present similar total distances. Then, as the carsharing fleet is reduced and its usage decays, the taxi service presents much higher distances. This is because as the number of taxis in the fleet is reduced, more distance has to be covered to pick each individual customer, as we commented in Section 3.3.2. Observing the number of unused vehicles it stands out a single carsharing transport which, as a result of its initial location, was not close enough to any of the customer to be used. Besides that, we want to remark the high distances of empty taxi journeys which are generally avoided with carsharing. Finally, the carbon dioxide emissions evolve in hand with travelled distances. Once again the trade-off among vehicle production pollution and vehicle usage pollution should be addressed. The number of vehicles in the fleet should be set at a level that increases its overall sustainability but is not so low as to increase the kilometres travelled by each vehicle further than a certain threshold.

## 3.4 Discussion

In this work, the experimentation has been performed through a multi-agent simulator. The combination of multi-agent modelling and simulation technologies seems appropriate to reproduce a system with a high degree of dynamism [47], such as the urban mobility one. Nevertheless, the data gathered from a simulation can be misleading if it is directly extrapolated to the actual system the simulation tried to reply to. Although we grounded all of our simulation scenarios on real data of Valencia, is it not possible to reproduce every detail, and thus concessions

have been made. Because of that, any conclusions drawn from our results must be understood within our experimental settings. That said, our results show a series of trends worth discussing and from which concrete action could be derived to improve the sustainability of urban traffic systems.

The impact carsharing technology could have on our environment is substantial. On the one hand, it reduces the distance that a service vehicle travels empty (not carrying any customer). This implies a more energy-efficient trip, as more customers are displaced per energy unit spent. In addition, it can avoid direct carbon dioxide emissions by implementing the service with fully electric vehicles. Regarding the latter, one of the objectives of the Spanish government is to increase the number of hybrid and electric-powered vehicles in their public taxi fleets. A 2019 study<sup>8</sup> indicates that the taxi fleet of Madrid, the capital of Spain, has a 26% of hybrid taxis meanwhile fully electrical vehicles account for only a 0.1%.

Our results show poor customer satisfaction with the carsharing services with respect to the taxi ones, although younger generations have positive perceptions on shared mobility [141]. The particularities of our free-floating carsharing proposal make it unfair to directly compare both types of fleet, as we commented above. Furthermore, we made strong assumptions with respect to the maximum walking distance and waiting time of our customers. Both magnitudes, while necessary to define the agents' behaviour in the simulation, in real life are likely to depend on many personal factors. Besides that, we believe a relocation service [122] for the carsharing fleet is essential to enable more users to make use of it. With accurate data of carsharing usage, the service provider could develop a relocation algorithm that allocates more cars in city areas where more demand is likely to be present according to the time of the day.

Besides the satisfaction, the type of user of each fleet must also be assessed. A dial-a-ride service such as taxis will always be needed, as some users will not drive a vehicle themselves. In addition, they might not be willing to, given the generally heavy traffic in cities and the lack of parking space in certain areas. Thus, potential users could be environmentally conscious people, tourists, users looking for savings, people with daily commutes that do not comfortably correspond to a

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<sup>8</sup>Movilidad urbana y metropolitana: un gran reto de las ciudades del siglo XXI, Observatorio del transporte y la logística en España: [https://observatoriotransporte.mitma.es/recursos\\_otle/monografico\\_otle\\_2019\\_movilidad\\_urbana\\_y\\_metropolitana\\_1.pdf](https://observatoriotransporte.mitma.es/recursos_otle/monografico_otle_2019_movilidad_urbana_y_metropolitana_1.pdf)

direct public transport line, among others. In general, users would tend to have a young to middle-aged age profile. A reduction in prices is not enough for a carsharing system to be attractive enough to the general public [54] (with respect to the commodity of dial-a-ride services). Moreover, a certain infrastructure [28] must be ensured so that customers do not feel insecure making use of the service. On the one hand, parking facilities must be implemented, for instance, by allowing carsharing vehicles to park inside city centres or having enough reserved parking spaces for this type of vehicle. On the other hand, a reliable network of electric vehicle chargers would come in hand both for users and service providers.

From all our experimentation, we want to highlight the hybrid simulations of Section 3.3.3. A city is a complex set of systems that interact with each other. The urban mobility system is one of the most complexes, as it contains several actors. Because of this, the hybrid simulations, those where the demand is covered by both a taxi and a carsharing fleet, are the closest to a real city representation. Most users of the urban traffic system have freedom of choice over different displacement alternatives. Our results suggest that there is potential to improve the general sustainability of our cities. The public should be encouraged to use more environmentally friendly options considering the freedom of choice. Combining transportation services with a strong promotion of the most sustainable ones could be the best approach.

The analyses our work presents are relevant for the mobility options of today. Nevertheless, the situation may change in the near future with the introduction of autonomous mobility. Such a mode of transportation would effectively turn traditional taxi and carsharing vehicles into autonomous, demand-responsive taxis. In this regard, there are a number of studies that address the effects of autonomous transportation services. For instance, in [136] authors study the implementation of an autonomous demand-responsive service that communicates the rural and urban areas of Bremerhaven (Germany). The authors suggest that operational and environmental costs significantly decrease if the individual transportation vehicles are completely replaced with such a service. However, they remark how the fully autonomous operation of the vehicles is key for the economic sustainability of the service. Another study [65] shows through a Melbourne (Australia) case study how travel demand could be met with only a small part of the current fleet if the mobility followed an on-demand autonomous shared transportation model. How-

ever, their results also present that the reduction of the vehicle fleet would increase the travelled kilometres of each vehicle, thus having a negative impact on the environment. This finding is also present in our experimentation. Ultimately, we want to remark that mobility is a really complex subject and changes that would seem to report obvious benefits may end up worsening the overall system once implemented. That is why simulation is especially important when it comes to exploring and testing mobility solutions.

## 3.5 Conclusions

In this research, we looked at the implementation of a carsharing system in Valencia, Spain, intending to provide a more sustainable alternative to the city's current taxi fleet. We have created simulations based on real-world city data for agent movement and distribution. Our findings show that, while some form of taxi service will always be required, carsharing has a significant potential to cut carbon dioxide emissions and traffic congestion in the city, albeit at the sacrifice of some consumer happiness.

With regard to the article's hypotheses, the experimentation shows a reduction in Valencia's taxi fleet is possible in terms of quality of service, which would be preserved. Nevertheless, this causes the sustainability of the fleet to worsen with respect to carbon dioxide emissions. On the other hand, after trying many configurations, we propose a fleet of 840 carsharing vehicles as a competitive alternative which presents a trade-off between customer satisfaction and sustainability. Finally, a hybrid solution that combines the usage of taxi fleets with green carsharing services is assessed. Such an option can meet all client demand while simultaneously reducing carbon emissions. This would be excellent for a transition to totally electric urban mobility, resulting in a more environmentally friendly city.

The urban mobility system of each city will have its own particularities. Many of them may heavily influence the usage of the different modes of transportation as well as their overall efficiency. Therefore, it is hard to state that our analyses of customer satisfaction can be transferred to other urban settlements. Nevertheless, we believe our general conclusions regarding the sustainability of reducing/replacing a taxi fleet with carsharing vehicles can be transferred to other cities of a similar

size to Valencia. In any case, our experimental framework can be used to simulate carsharing fleets in any city, provided we have data to guide the demand generation, and thus we recommend experimenting before transferring any conclusions.

The current work paves the way for future research in various directions. On the one hand, we would like to look at more practical demand generation methods. This would involve a dependable data source and the subsequent choice of convenient features. On the other hand, we wish to add another mode of transportation to our simulations to examine the proportions of overall mobility demand that each system covers in greater detail. Vehicles from Valencia's public transportation system, such as buses, bikes, and metro lines, would be an excellent addition to improve simulations of city mobility. Finally, we will enhance the simulation regarding carsharing systems by adding vehicle relocation, a specially relevant feature for free-floating carsharing. Specifically, we want to develop a machine learning prediction solution, similar to the one presented in [102], that aids to determine the time of day when the relocation should take place as well as new vehicle locations.





## **Part III**

# **Urban Transportation Enhancement**



# Best-Response Planning for Urban Fleet Coordination

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### Abstract

*The modelling of fleet vehicles as self-interested agents brings a realistic perspective to open fleet transportation research. This feature allows us to model the fleet operation from a non-cooperative point of view. In this work, we study parcel delivery in a city with limited resources (roads, charging stations). We designed and implemented a system composed of a multi-agent planner and a game-theoretic coordination algorithm: a Best-Response Fleet Planner. The system allows for the self-organisation of the transportation system by coordinating a fleet of self-interested electric vehicles. The system's operation is optimised together with resource usage while preserving the agents' private interests, allowing each agent to plan its actions. The results show that our system has higher scalability than similar approaches, allowing it to function for a considerable number of agents in settings that feature congestion and conflicts. Additionally, overall solution quality is improved compared to other coordination systems, reducing congestion and avoiding unnecessary waiting times.*

## 4.1 Introduction

A city can be seen as a non-cooperative or competitive scenario. Many of its resources, like road networks or petrol stations, may get congested if too many users want to use them simultaneously. As users (generally drivers) act selfishly and uninformedly, resource management tends to be poor. This translates into traffic congestion, higher waiting times to refuel, and, in general, more air pollution and less quality of service (for transportation service users).

Optimisation techniques can improve systems by identifying and minimising inefficiencies, reducing waste, and maximising output. These techniques use mathematical and computational models to analyse data and identify areas of improvement [124, 26], such as minimising production costs, reducing delivery times, or improving quality. In transportation systems, for instance, optimisation techniques can be used to optimise routing, minimise fuel consumption, and reduce transportation time, resulting in improved delivery performance and reduced costs. One of the main limitations, however, when it comes to traffic optimisation, is gathering the necessary information to coordinate every user's actions and make intelligent decisions. Connecting all services and infrastructure would be beneficial for such a complex task. Smart City technology would allow data collection and exchange among these services. This data could be used in research on improving urban traffic and applied to develop solutions.

The aforementioned technologies can be applied to develop an intelligent, self-organising transportation service. This work focuses on *open* delivery fleets, dynamic fleets whose number of vehicles can increase or decrease according to the demand. In contrast with traditional fleets, the drivers are autonomous: they choose the passenger or delivery to serve and obtain a benefit accordingly. Although drivers belong to the same fleet, they act according to their benefits. Therefore, when reproducing such a fleet, we must ensure that the agents make their own decisions and are not coordinated by a centralised entity. The transports that compose the delivery service must be able to self-organize themselves according to their private goals, but taking into account they all coexist in the same scenario, and thus it is in their best interest not to cause congestion. Considering these features, Agent-based modelling (ABM) and Game theory are applied to reproduce this type of fleet. ABM [123] is a computational modelling technique used to simulate com-

plex systems consisting of multiple interacting agents. In ABM, each agent in the system is programmed with a set of rules that govern their behaviour and decision-making processes. Game theory [154], on the other hand, is defined as the study of mathematical models of strategic interaction among *rational decision-makers*; i.e., agents who make decisions based on personal benefit. Game theory provides the tools to coordinate the fleet's autonomous transports taking into account the actions of each other.

Our work presents a practical application to coordinating self-interested vehicles of a fleet. In addition, this coordination considers the resources of the urban area where the fleet operates to optimise its use and avoid congestion. To this end, we have, on the one hand, designed and implemented an ad-hoc optimal planning algorithm that enables each fleet's individual vehicles to plan their actions according to their interest. Moreover, the planner considers every other vehicle's plans to obtain the optimal plan with respect to every other agent's plan. This, in turn, implies the avoidance of congestion and conflict resolution. On the other hand, we have implemented a game-theoretic coordination algorithm (best-response dynamics) which converges to an equilibrium: A collection of agent plans from which no vehicle is incentivised to change. The fleet's operation that describes the equilibrium ensures the vehicles perform their services to maximise their benefits, implying that their private interests are preserved.

The main differences between our approach and other fleet coordination techniques are the following. On the one hand, decentralised coordination is provided. Generally, fleets are coordinated by a central entity that decides the actions of each vehicle. In contrast, our fleet vehicles have the autonomy to make their decisions. In addition, vehicle coordination may occur even if a member fails to communicate, thus being appropriate to model an open fleet. Finally, our approach enables each vehicle to keep its goals private, which is useful when coordinating agents in a non-cooperative scenario. On the other hand, using game theory techniques allows us to define the use of the city's resources as a congestion game which, in turn, shows the agents (vehicles) that it is in their best interest to make better use of them. With these features, we achieve the optimisation of the whole system together with the preservation of the agent's autonomy, which is generally lost in other coordination approaches.

Our research explores the limitations of the proposed system through extensive

experimentation. We show the extent to which the ad-hoc planner can return optimal plans in a reasonable time according to problem complexity and the number of agents. The results indicate that the system overcomes similar approaches in terms of computation power, taking into account the advantage of having an ad-hoc planner. Our system proves the viability of simulating realistic scenarios, with a significant number of agents, in a game-theoretic environment. Finally, we assess the quality of the returned solutions, which are better than those obtained by greedy coordination.

The remainder of the paper is organised as follows. Section 4.2 reviews related work. Then, in Section 4.3, we present an overview of the entire proposed system. Next, Section 4.4 specifies the urban mobility planning domain that reflects the problem to be solved. Section 4.5 describes in detail the developed ah-hoc planner. Following, the best response fleet planning (BRFP) process with which the whole game is developed to reach an equilibrium solution is explained in Section 4.6. The experimental results of the proposed work are presented in Section 4.7. Section 4.8 discusses urban transportation challenges, how our system applies to other problems, and its limitations. Finally, Section 4.9 draws the conclusions of this work and presents possible future research directions.

## 4.2 Related Work

The proposed system is related to three fields within artificial intelligence: Multi-agent systems, automated planning, and game theory. In this case, techniques of each branch are applied to an urban mobility domain intending to optimise the operation of delivery fleets. Multi-agent systems and their simulation allow us to reproduce the behaviour of human drivers in a software world and study their actions and any synergies that may arise. Moreover, automated planning algorithms ensure that, given an agent's current knowledge, they are able to compute their best course of action, considering each possible path at each computational step. Finally, knowing they are part of a competitive environment and assuming rationality on all other participants, game theory gives the basis to reach agreements and equilibria among the actions of all agents in the scenario.

### 4.2.1 Multi-agent Simulation

Multi-agent simulation (MAS) is a computational modelling technique that allows the simulation of complex systems composed of multiple interacting agents. Applied to urban fleet management, MAS is used to model and analyse the behaviour of a fleet of vehicles in a city, considering various factors such as transportation demand, traffic conditions, and resource availability. MAS can help improve the efficiency and sustainability of the transportation system by allowing fleet managers to test different scenarios and strategies in a safe and controlled environment before implementing them in the real world. MAS has been widely used to model and simulate vehicle fleets [72, 148, 32]. An urban mobility domain must define many different interactions among the various elements of the scenarios. MAS help achieve that, as we can represent each element through an agent (vehicles, pedestrians, charging stations, etc.) and define appropriate behaviours for them. In [117], authors presented a MAS-based simulator specialised in the representation of urban fleets of different kinds. Later, in [94], the aforementioned simulator was extended to include new types of fleets, such as carsharing. Using simulators enables us to explore the effect of different coordination paradigms on the operation of a fleet without having to implement changes in the real world.

In recent years, new agent-based simulators have appeared that facilitate the development of different strategies for fleet management in the urban environment. One of the tools is SUMO [86], an open-source traffic simulator that can be used for route choice, communication between agents and infrastructure, traffic management, and autonomous driving. SUMO uses an origin/destination matrix to assign movement between city zones. Another tool is MATSim [155], a framework for demand modelling and traffic flow simulations. SIMmobility [4] is another simulation tool that focuses on mobility demand impact prediction for smart shipment services. Finally, commercial tools like VISSIM [46] offer an array of technologies to address multiple mobility and transportation problems.

### 4.2.2 Fleet Coordination & Game Theory

Regarding vehicle fleet coordination, the degree of freedom given to each vehicle is crucial. Such a degree indicates how much the self-interest of the vehicle (or



its driver) can influence its actions. Authors assess this topic in [92], where a taxonomy of autonomous vehicle coordination problems is presented. According to the degree of freedom given to each vehicle, the coordination approaches vary from fully *centralised*, where an external entity imposes actions on every fleet vehicle, to fully *emergent*, where its self-interest guides all of the vehicle's actions.

There is no direct involvement of the agents (vehicles, drivers) in any coordination protocol in emergent coordination approaches. Agents behave according to their goals and aim to maximise their actions' utility. These features give rise to the use of game-theoretic techniques, where each agent assumes the rationality of the others and determines its actions based on the information it knows or can guess about other participants.

For instance, the work in [163] presents a distributed approach for coordinating the charging of a large fleet of plug-in electric taxis in a city, aiming to reduce charging costs, improve charging station utilisation, and balance charging requests for the power grid. The approach involves a two-stage decision process with a thresholding method for charging time slot selection and a game-theoretical approach for charging station selection, as validated by extensive numerical simulations. Similarly, the paper [52] discusses the problem of fleet configuration for unmanned vehicles, focusing on optimising the fleet for minimum costs. The proposed approach involves transforming the fleet configuration activity into an optimisation problem using game-theoretic techniques, with the aim of achieving interoperability among different organisations involved in fleet provision through distributed and decentralised planning.

Therefore, emergent coordination is generally applied to fleets composed of independent vehicles; in other words, non-cooperative fleets. In these fleets, like those of Uber, Lyft, or Glovo, each driver obtains benefits thanks to his/her work. Even if they belong to the same fleet, the different drivers do not tend to cooperate, although that does not imply that they are competitive either. For our work, we will assume non-cooperative (agents only care about maximising their utility) and non-strictly competitive (agents do not actively look to reduce the utility of other agents) self-interested agents.

### 4.2.3 Automated Planning

Self-interested agents must be able to plan their actions according to their private benefits. Because of that, we introduced Automated Planning to the system. A planner generally looks for a feasible, somewhat optimised solution to a problem. This applied to a fleet would imply centralised coordination, as the planner would define each vehicle's actions. Nevertheless, the planning goal can be distributed into different tasks, allowing each agent to plan, by itself, how to carry out their task. When planning is applied to MAS, we perform Multi-Agent Planning (MAP) [157].

In recent years, there has been significant research on cooperative MAP, where agents join their efforts to achieve a common goal. Cooperative MAP is used to solve tasks that can not be performed by a single agent or are better solved when several agents work together [40]. In some cases, agents with different abilities must cooperate to solve a planning task [147]. However, we focus on types of MAP where game theoretic techniques may be applied. These are the coalitional MAP, where establishing alliances benefits groups of agents [39]; adversarial MAP, which features self-interested agents with opposed goals and, consequently, takes place in strictly competitive scenarios; and finally, non-cooperative MAP, in which agents are not strictly competitive and; therefore, they are prone to follow a collaborative strategy and resolve conflicts.

The coordination of self-interested agents in non-cooperative settings is generally performed through a game. In this game, the agent strategies are their plans, the actions they intend to do. These plans will be adapted to other agents' plans to avoid conflicts. Finally, an equilibrium is obtained: a union of agent plans (joint plan) that ensures no agent will deviate from it. The equilibrium, in addition, must solve the goal of the MAP task. The works in [70, 74] introduce FENOCOP, an approach to solving non-cooperative planning problems. In this approach, agents have a limited set of plans. The final joint plan is built in two phases or games: first, a Nash Equilibrium [110] is obtained from the many combinations of agent plans. Then, a scheduling process delays specific actions to obtain an executable outcome, avoiding conflicts. This approach can obtain Pareto Optimal and fair equilibria, an extra quality measure for the solutions. However, the methods lack scalability because of their exponential complexity.

Another work, presented in [73], describes the so-called *Better-response Planning Strategy (BRPS)*, a game-theoretic algorithm to solve *congestion games* [129]. In congestion games, the scenario features a series of resources that agents will use. When too many agents use a resource simultaneously, it gets congested, and its cost increases. Congestion games can significantly represent urban mobility domains, as these contain many resources (roads, charging stations) in which we wish to avoid congestion. In a best-response process, an equilibrium is reached through an iterative process in which the participant agents propose, in turn, a plan which is a *best-response* to every other agent's plan. This process finally converges when no agent is incentivised to change its plan. The Better-response Planning Strategy of [73] allows agents to propose not their best plan but simply a plan that improves the utility of its previously proposed plan. This avoids the need for optimal planning that a best-response process requires, which is computationally more costly than satisficing planning in practice [5].

Our approach is inspired by the Better-response Planning Strategy but uses a best-response process, as we can perform optimal planning in a fast manner thanks to the design and implementation of our ad-hoc planner. We apply these methods to coordinate the operation of an open delivery vehicle fleet, ensuring optimal delivery routes and resource congestion avoidance.

## 4.3 System Overview

The work described in this paper is motivated by the research on rational, self-interested agents. An agent with those features has its private objectives, which, in practice, translates to its unique utility function. Our goal is to explore the coordination of urban fleets composed of self-interested agents, particularly electric delivery vehicles. Such vehicles may belong to a fleet, thus serving customers' delivery requests and getting compensated by it. Introducing delivery vehicles in a city with limited resources creates a competitive scenario where agents compete to deliver their parcels as soon as possible. However, we must ensure that the aforementioned scenario (delivery service) is solvable, avoiding the conflicts that generally arise between agents. For that, we model the operation of the agents as a MAP task, precisely a non-cooperative MAP task in a non-strictly competitive

setting, one in which agents do not create coalitions to solve the global goal of the task but instead, the task is solved by coordinating how agents solve their goals. In this way, we aim to obtain a functioning of the agents which preserves their individuality, not imposing any action but allowing them to determine their actions by themselves and simultaneously avoid conflicts with the rest of the agents of the scenario.

In a delivery fleet with the aforementioned modelling, the global goal would be to complete all delivery tasks, thus solving the scenario. On the other hand, the agents that compose it will aim to maximise their utility, dropping off the parcels as soon as possible while following the most efficient route: the one that involves less travelled distance and power consumption. To avoid conflicts, the actions of each agent are decided by a game-theoretic process: A Best-Response Fleet Planning (BRFP) process (Section 4.6). The process begins by creating a congestion game equivalent to the scenario to solve. For this game, the moves or strategies of the players will be their actions, i.e., an ordered list of the actions they will do. This list of actions is a plan, being the plan's goal to get the highest possible utility out of the actions. Therefore, transport (delivery) agents act as players whose strategies are plans built according to their interests.

To compute such individual plans, we developed an ad-hoc planner (Section 4.5). It is ad-hoc as it is designed to solve problems set in the Urban Mobility Planning Scenario (Section 4.4). We take advantage of the domain characteristics to speed up the search. All in all, given a scenario and a transport agent in that scenario, the ad-hoc planner builds the optimal plan for such an agent, taking into account both the state of the scenario and the plans of every other agent, always obtaining a plan that is the best response to all other agents' plans.

Once the congestion game is established, it is developed by the BRFP process, in which the agents propose different strategies (plans), always in the best response, improving each turn (if possible) their previously proposed plans to (1) avoid conflicts with other agents and (2) minimise their costs. The process converges to an executable solution (joint plan), a Pure-strategy Nash Equilibrium (PNE) [105], guaranteeing that no agent will deviate from it (change its strategy). In this way, the BRFP obtains a solution that indirectly achieves the global goals of the fleet (all transport agent's delivery tasks are served) by capitalising on the agents' own incentive to maximise its benefits, which it does by completing the

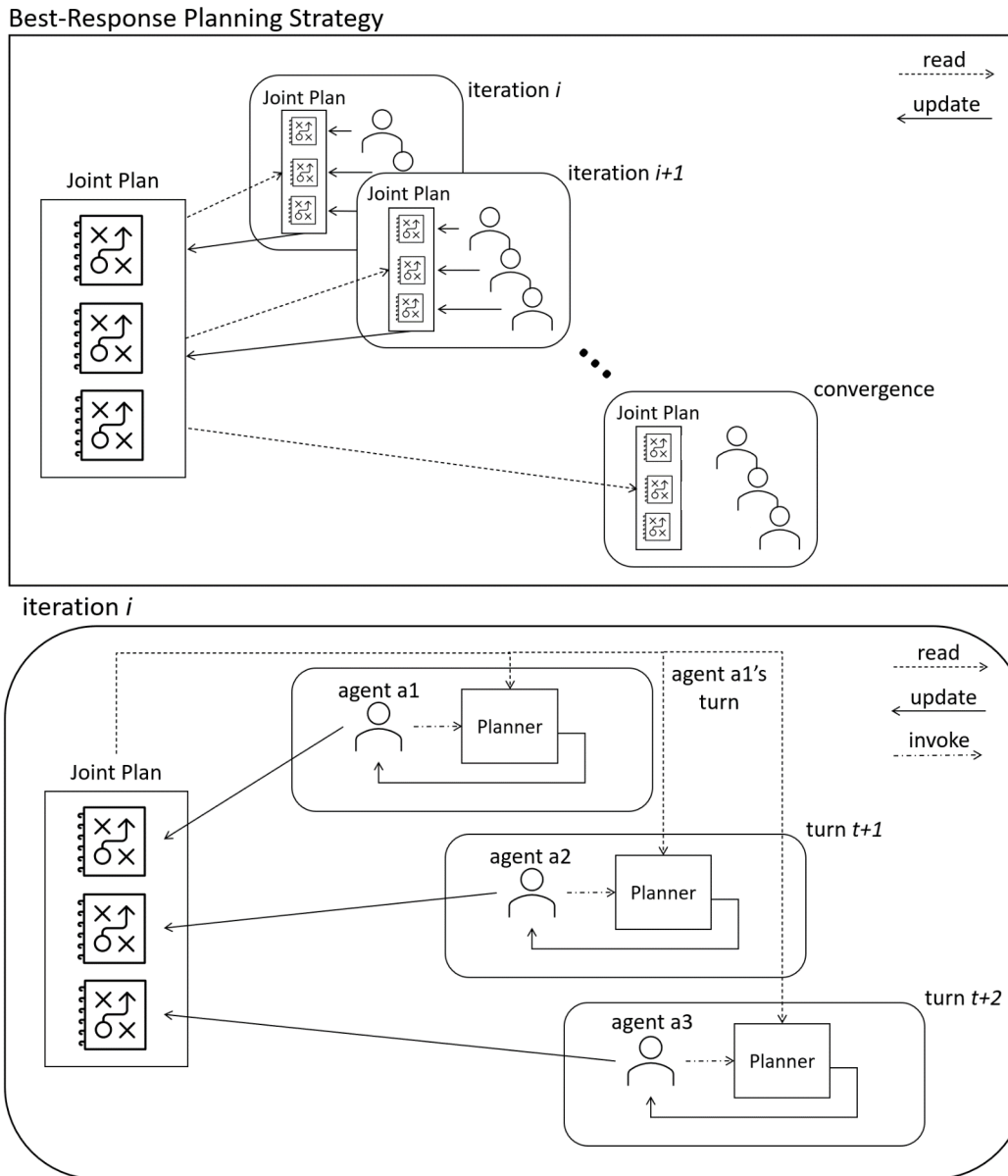


Figure 4.1: Graphic of the functioning of the Best-Response Fleet Planner. The image at the top shows how the Joint plan is updated each iteration: All agents compute their plans and update a copy of the joint plan sequentially. The process converges when no agent changes their plan. The image at the bottom shows an iteration in detail; each agent invokes the ad-hoc planner during its turn to propose their best plan, updating the Joint plan if necessary. The planner considers all other agents' plans by reading the joint plan each time it is invoked.

tasks following the optimal route and avoiding congestion. As the global goals are satisfied, the obtained joint plan also coordinates the fleet's operation, which could be simulated.

The diagram in Figure 4.1 shows the operation of the BRFP. It can be seen how the agents use the planner to propose their best strategy. In one iteration, every agent has to propose a new best plan (if the previous one was not in best-response already), updating the joint plan. If, after a whole iteration, no agent has changed their plan, the process has converged, and the joint plan, the union of every agent's individual plan, is returned. The joint plan describes a solution to the congestion game, which is an equilibrium and, in addition, ensures the lack of conflicts among agents of the scenario. In the following sections, we describe the planner and BRFP algorithm and the urban mobility planning domain in which the executions occur.

## 4.4 Urban Mobility Planning Scenario

The planning problems of this work are set in an urban mobility scenario that models a real-world smart-city urban area. The scenario contains three types of elements: *parcels*, with an associated initial position and final destination; electric delivery vehicles or *transport agents*, with an initial position and a current travel capacity (electric power), expressed in kilometres; and finally, electric *charging stations*, which have a certain number of charging poles for the transports to recharge their batteries and an electric power which determines the speed at which agents charge in them.

We are modelling a delivery service with non-fixed pick-up or drop-off locations. Transport agents have two basic behaviours: complete a delivery task, which involves moving to the parcel location, picking it up, driving to its destination, and recharging their batteries by driving to a charging station. Transports can carry a single (1) parcel at a time. Consequently, our system considers the following four types of actions:

1. PICK-UP: Move to a parcel's position and pick it up.
2. MOVE-TO-DEST: Move to the carried parcel's destination and drop it off.
3. MOVE-TO-STATION: Move to a charging station and wait for the charge.

#### 4. CHARGE: Begin charging until the travel capacity is full.

Actions 1 and 2 constitute a *delivery service* while actions 3 and 4 constitute a *charging service*. These services must be executed without interruption; consequently, during the construction of the individual plan of a transport agent, actions of types 1 and 2 will always appear consecutively. The same applies to actions of types 3 and 4. A scenario will be solved once the delivery tasks assigned to every transport are completed. In practice, a transport agent with a preassigned number of delivery tasks will aim to follow the optimal order to complete them so that delivery time and power expenses are minimised.

We have chosen to apply this system to a delivery fleet. Nevertheless, our approach can be used for other applications in the field of urban mobility, such as the coordination of fully autonomous vehicles. In addition, it could be adapted to manage the operation of other distributed systems in which the self-interest of each part must be considered.

### 4.4.1 Transport Agent's Utility

Transport agents are modeled as rational, self-interested agents that act according to their private interests. Such an interest is to maximise their utility. Transports must complete all their delivery tasks regardless of the cost involved. Because of this, an agent's utility is equivalent to the negative value of its costs. Thus, transports are motivated to complete their tasks minimising their total cost.

The costs arise from two main sources: customer waiting time or *waiting cost* and resource congestion. Regarding the former, transport agents have their costs incremented by a fixed amount every time instant a delivery task assigned to them remains uncompleted. Concerning the latter, roads and charging stations represent resources whose use incurs costs. These resources may get congested if too many agents use them simultaneously (in overlapping time intervals). If a congested resource is used, the cost of such usage will be higher than expected. Resource congestion costs are identified as *road cong* for road network congestion and *power cong* for electric power network congestion in Equation 4.1.

The exact formulas that describe congestion costs can be configured by the user. Generally, a resource will have a certain *resource bound* defining the number of

simultaneous uses it can withstand. Once that bound is surpassed, the resource's cost increases proportionally to how many agents use it. Our modelling defines two resource bounds: *power bound*, for power network congestion, and *road bound*, for road network congestion. Let us define a bound, for instance, of 0.5. For power network congestion, that would indicate the network gets congested once 50% of its power is drawn at a time. In contrast, road network congestion would indicate a road is congested once 50% of its capacity is used at a time.

The *total cost* of a transport agent is used to evaluate its plan. It is computed as the addition of its *waiting cost* and the *costs derived from resource congestion*, if any. In addition, every type of equation cost is pondered by a *weight*:  $w_w$ ,  $w_r$ , and  $w_p$  for waiting, road congestion, and power congestion costs, respectively. The utility of an agent, described in Equation 4.1, is equal to  $-(total\ cost)$ , which, in time, is the utility associated with its plan.

$$(4.1) \quad U = -(total\ cost) \\ = -(waiting\ cost \cdot w_w + road\ cong \cdot w_r + power\ cong \cdot w_p)$$

With this modelling of costs, we achieve transport agents interested in completing their assigned delivery tasks in an order that involves less delivery time, fewer power expenses, and avoids congestion when it is profitable.

#### 4.4.2 Conflicts

A shared scenario, populated by self-interested agents and with a limited number of resources, may give rise to conflicts among agent plans. A conflict makes the involved agents' plans unfeasible. Our domain presents *charging station conflicts* when two or more agents plan to recharge in the same charging station during overlapping periods, and *the station does not have enough available charging poles to serve all transports simultaneously*. In this situation, the agent that arrives at the station the soonest has its charging spot ensured. Therefore, the conflict resolution falls to the rest of the agents, who will have to choose between waiting in line at the station for their turn to charge or charging at another station.

Conflict resolution always involves an increase in the agent's delivery time and, therefore, costs. However, there is no way in which conflicts could be permitted.



To ensure agents avoid and/or resolve conflicts, any agent whose plan is in conflict will be penalised with a great increment of its costs.

### 4.4.3 Individual Plans and the Joint Plan

Agent actions are reflected in plans. A plan consists of a list of entries arranged in ascending order according to their start time. Every plan entry corresponds to one action and presents it with its attributes and initial and end time in seconds. An example of a joint plan (the union of agents' individual plans) in our domain can be seen in Table 4.1.

Table 4.1: Visual representation of a joint plan. Each row corresponds to a plan entry. On the left column, the initial time instant of the action is presented in seconds. In the middle one, the action with all its attributes. On the right column, the time instant in which the action finishes is indicated, also in seconds.

<b>init time</b>	<b>actions</b>	<b>end time</b>
0.00	(Agent_A, MOVE-TO-STATION, station1)	4.62
0.00	(Agent_B, PICK-UP, parcel1)	9.81
4.62	(Agent_A, CHARGE, station1)	9.97
8.52	(Agent_C, PICK-UP, parcel3)	17.51
9.81	(Agent_B, MOVE-TO-DEST, parcel1)	16.07
9.97	(Agent_A, PICK-UP, parcel2)	19.01
17.51	(Agent_C, MOVE-TO-DEST, parcel3)	25.41

We must differentiate between two types of plans: *individual* or agent plans, and the *joint* plan. Individual plans are the ones planned and executed by a single agent. The joint plan, in contrast, is the union of every individual plan. Individual plans are computed guiding the planning only by the agent's private interests, i.e., minimising its costs. However, when part of the joint plan, the individual plan may have actions in conflict. All the conflicts must be resolved for a joint plan to be executable.

## 4.5 Ad-hoc Planner

Considering the characteristics of the urban mobility domain defined above, we decided to implement an ad-hoc planner. Agents invoke an instance of the planner to obtain optimal individual plans that solve the problem scenario while ensuring their actions avoid conflicts. The current world state is represented by the transport agent's knowledge at the moment of planning. This includes its current position and travel capacity as well as its uncompleted tasks. In addition, because of the associated best-response process, the agent will have complete information on the plan in the joint plan of every other agent in the scenario. The planner uses this to avoid conflicts.

In this section, we describe our planner's elements, its search tree's components, and the procedure used to build and explore it.

### 4.5.1 Best-response Planning

Our planner is meant to be used by the agents participating in a best-response process to obtain and propose their best strategy; that is, the best possible plan with respect to every other agent's plan. Because of that, our planner performs optimal planning, which is reasonable given the restrictions of our domain. Hence, the individual plan returned from the planning process is always the best response to the plan of every other transport agent. When a plan is returned, the agent proposes it and is added to the joint plan, updating it.

Each planner instance has its own *station usage table*, a data structure containing, for every charging station in the scenario, the agents that planned to use it together with the time instants they arrive at it and start and finish the charge. An example of such a structure can be seen in Table 4.2. This data structure is used to detect charging conflicts at the end of a best-response turn and makes agents avoid them in their subsequent planning processes.

The best-response process will eventually converge to a Pure-strategy Nash equilibrium (PNE) [105]. Once the best-response process converges, the joint plan is guaranteed to be a PNE, conflictless and, thus, executable.

Table 4.2: Station usage table example. It reflects the information regarding charges that appear in the joint plan. For every station, it contains a list with the agents charging in it and the time instants in which they arrive at the station, begin and finish charging.

<b>station</b>	<b>agent</b>	<b>arrival</b>	<b>charge start</b>	<b>charge end</b>
station1	agent1	17.38	17.38	21.38
	agent3	19.56	21.38	26.38
station2				
station3	agent2	5.54	5.54	15.54

## 4.5.2 Partial Plan Search Tree and Exploration algorithm

Our planner searches for the optimal plan by building and expanding a search tree of partial plans following an A\* algorithm. During this process, the most promising nodes are expanded depending on both the utility of the partial plan developed so far and the potential (optimistic) utility that the rest of the plan could develop from that node. The nodes of the tree contain partial plans. Nodes expand and generate children, which inherit their plan and add new actions.

Nodes can be of two types: *parcel* or *charge* nodes. A *parcel* node is created for each uncompleted delivery task of the agent when expanding the parent node. *Charge* nodes are created whenever the agent's travel capacity is not maxed out in the parent node. One charging node is created per reachable charging station in the scenario. The information of each station is accessed through the *station usage table* (Section 4.5.1). With it, the planner sets the time instants at which the agent will reach the station and start charging, according to the available poles and the charge duration.

By creating parcel and charge-type children, plans are built adding two actions to the parent node's partial plan in each step. Using this method, we only consider the addition of necessary and feasible actions every time. Consequently, we are avoiding search tree ramifications that would eventually be discarded either because of conflicts or a low utility value.

### 4.5.3 Plan Evaluation

The value of a plan is tied to the utility it reports to the transport agent that executes it and, therefore equivalent to the  $-(total\ cost)$  described in Section 4.4.1. Globally, a joint plan is not evaluated, as only its feasibility is relevant. The planner (the individual instance of an agent planner) evaluates *partial* plans during the plan-building process and *complete* plans to return the best solution. Any congestion in which the agent might be involved is considered during the plan evaluation, increasing its cost accordingly.

To evaluate a partial plan  $n$  Equation 4.2 is used, where  $g(n)$  is its cost,  $h(n)$  is an optimistic calculus of the expected cost that completing every non-completed goal would yield, and  $h^*(n)$  is the optimal cost to reach all non-completed goals from node  $n$ .

$$(4.2) \quad f(n) = g(n) + h(n), \quad h(n) \leq h^*(n)$$

The heuristic function  $h$  is a relaxation of the problem constraints. It assumes that, from a particular partial plan, the remaining delivery tasks can be completed as efficiently as possible without the need to charge. This is done by computing the *best permutation*; the order in which to attend the remaining delivery tasks that minimise costs. The node's heuristic value will estimate the minimum cost of completing the rest of a plan. The heuristic estimate would only match the actual cost of a plan if such a plan was completed without charge actions and the agent was not involved in any congestion.

The value of a complete plan  $n$  is equal to  $g(n)$ . When an agent proposes its plan, it gets integrated into the joint plan. Such a plan may present conflicts as a part of a joint plan. If the integration does not cause any conflicts, the plan's value will be the same as it had when proposed. However, when a plan causes any conflict, its cost is highly increased, forcing the planner to change it in the following planning turn.

### 4.5.4 Search Tree Pruning

Planning is a computationally hard task. Our planner implements mechanisms that aid in speeding up the plan search process and lower memory consumption.

**Best solution prune.** Once the first solution node is found, its plan is extracted, evaluated, and its utility saved as the *best solution value* found so far. This value is updated as new solution nodes are reached. If the value of a child node is worse than the best solution value, it will be discarded. The partial plan of an open node with an f-value below the best solution value has no potential to evolve into a better solution, so the planner can avoid wasting computational power expanding it.

**Previous plan utility bound.** When an instance of the planner is created, the invoking agent's previous plan (found in the previous best-response iteration) can be passed to it. If there is a previous plan and the utility it reports is higher than 0, such a value will define a lower bound value for the planning process. When a node is evaluated, it will be discarded if its value is below the lower bound. In this way, solution nodes that contain worse plans (or partial plans with no potential to improve) than the previously obtained ones are not considered, speeding up the process. This technique is only applied if the previous plan of an agent is not causing any conflicts.

## 4.6 Best-response Planning

This section explains how the best-response planning process is developed. First, it describes the iterative process in which the agents propose their best plan given the plans of the other agents. Then, the way to resolve conflicts that may arise between agents during this process is explained. Finally, we explain how to build an initial joint plan with a greedy algorithm.

### 4.6.1 BRFP Process

The BRFP is a process in which an agent  $a$  iteratively looks for a plan  $\pi^a$  which is in best response to every other plan in the joint plan  $\Pi$ . At the beginning of the process, an arbitrary order is defined among all participant agents, and an empty joint plan  $\Pi = \emptyset$  is created. Alternatively, the process can begin from an initial joint plan  $\Pi = \langle \pi^{1'}, \pi^{2'}, \dots, \pi^{n'} \rangle$ , where  $\pi^{a'}$  is a non-optimal plan created following a greedy strategy (see Section 4.6.2). This provides the agents with a lower utility bound (see Section 4.5.4), speeding up the planning during the first BRFP iteration.

During the process execution, agents must best respond in each iteration. A planning process is used for that, which can return either a new plan, the same plan as the previous iteration, or nothing if there is no solution. If the same plan is returned, the agent will preserve it since it means that it is still in the best response to every other plan. When no agent modifies its plan in a complete iteration, the BRFP has converged to a joint plan that is a PNE.

From an agent's perspective, the BRFP works as follows:

- An arbitrary order between agents is established. Following such order, an initial joint plan is built incrementally using the individual planner of the agent or following a greedy strategy:  $\Pi = \langle \emptyset, \dots, \emptyset \rangle$ ,  $\Pi = \langle \pi^1, \emptyset, \dots, \emptyset \rangle$ ,  $\Pi = \langle \pi^1, \pi^2, \dots, \emptyset \rangle$ , ...,  $\Pi = \langle \pi^1, \pi^2, \dots, \pi^n \rangle$ .
- In one iteration  $i$ , agent  $a$  executes these steps:
  1. Analyze the utility of its current plan  $\pi_{i-1}^a$  in the joint plan, defining a lower bound for the following search.
  2. Start a planning process to search for a new plan  $\pi_i^a$  which is in best response to every plan in the joint plan.
  3. If a new plan is returned, update the joint plan:

$$\Pi = \langle \dots, \pi_{i-1}^a, \dots \rangle \rightarrow \Pi' = \langle \dots, \pi_i^a, \dots \rangle$$

In case no plan with higher utility than the lower bound can be found, the agent keeps its previous plan  $\pi_{i-1}^a$ , since it is still in best response.

- When no participant agent changes its plan in a complete iteration, the process has converged, and the current joint plan is a PNE.

### 4.6.2 Initial Greedy Joint Plan

The complexity of our planning scenarios is proportional to the number of parcels and charging stations that they include. The planning during the first iteration of the BRFP process is considerably slower. The absence of previous individual plans implies not being able to use the previous plan utility bound (Section 4.5.4). We

implemented a greedy method that creates an initial plan for every agent to palliate this. Such a greedy plan provides the first best-response iteration with a utility value to prune the search tree. The greedy plan is built as follows:

While there are uncompleted delivery tasks:

1. Select the parcel with a pick-up location closest to the agent's current location.
2. Check if the agent has enough travel capacity to complete the delivery.
  - 2.1 If it does, go to (3).
  - 2.2 If it does not, the agent goes to the closest station and charges. Then goes back to (1).
3. Complete the delivery task of the selected parcel (pick-up and drop-off).

The cost of the initial greedy plan will be higher or equal to that of the optimal plan but never lower. The creation of an initial greedy joint plan has proved to be very effective, significantly reducing the amount of generated nodes during the first planning process. However, it influences the BRFP process, as it guides it towards certain equilibria, avoiding others that can not be reached with the method's restrictions.

## 4.7 Experimental Results

The described solution has been implemented with Python 3.7. Among the employed Python modules, Shapely, Geopy, and Geojson stand out, as they were employed to reproduce real-life road networks, calculating travel distances and times over the city area where the vehicle fleet is deployed. Transport routing is solved by the Open Source Routing Machine [89], a routing service that calculates, among others, the fastest route between any two given points. Each problem configuration was encoded in JSON format, indicating the attributes of each of the actors (agents, resources) of the problem together with their location in the city.

Finally, the multi-agent simulator SimFleet [117] was used to load and visualize the problem configurations, although it had nothing to do with their resolution.

To test our system, we defined a set of 13 problem configurations, presented in Table 4.3, with different levels of complexity. The complexity of our problem is defined by the number of transport agents, the number of delivery tasks or parcels an agent must complete, and the number of charging stations. The number of parcels per agent (P/A) increases planning variability. Charging stations have the same effect. Therefore, as those values increase, the complexity does too. The number of agents mainly affects the performance of the best-response process, as more agents imply longer iterations and more conflicts to resolve. All charging stations belong to the same power network, whose maximum power is the addition of each station's power.

The main area of the city of Valencia, Spain, was chosen as the scenario for all the problems, and the agents used its road network. Distances among scenario elements are determined by their location in the city and expressed in meters. The speed of every transport agent is fixed. Figure 4.2 shows a visual representation of a problem in our urban mobility domain. The initial position of transport agents and parcel positions are defined according to a probability distribution computed from various city data, including population, traffic intensity per road, and geolocalised social network activity. Please note that each transport has been assigned its packages already. Thus, the problem we are dealing with is the coordination of their delivery.

Such a heterogeneous set of problems aims to show both our system's capability and limits. Therefore, we first compare the performance of our planner against other similar approaches. Then, we address the quality of our solutions to show how our approach optimises the urban traffic system. Finally, we demonstrate the interest in modelling resource congestion and how self-interested agents can be incentivised to avoid it.

Unless otherwise indicated, the default values of the different variables affecting the agents' utility are those presented in Table 4.4. The base price of power is established, as well as the standard power consumption for electric vehicles. In addition, a unit cost for waiting time is defined. Finally, the congestion bounds of the different resources are indicated following their modelling in Section 4.4.1.



Table 4.3: Problem instances used for experimentation. Row values indicate the number of transport agents, parcels, parcels per agent (P/A), stations, and charging poles in the scenario, respectively.

Problem	Transport agents	Parcels	P/A	Stations	Charging poles
p20-60	20	60	3	20	40
p20-80	20	80	4	20	40
p20-100	20	100	5	20	40
p50-150	50	150	3	20	40
p50-200	50	200	4	20	40
p50-250	50	250	5	20	40
p100-200	100	200	2	30	60
p100-300	100	300	3	30	60
p100-400	100	400	4	30	60
p150-300	150	300	2	30	60
p150-450	150	450	3	30	60
p200-400	200	400	2	30	60
p500-1000	500	1000	2	30	60

### 4.7.1 General Performance

In the first set of experiments, we show the performance of our planner in terms of time to achieve a solution. For that, we solved the problems presented in Table 4.3 and measured the number of iterations the best-response algorithm needed to converge, the total running time of the BRFP, and the average time that each individual planner instance took to return a solution. We also indicate the time per iteration since it is helpful to estimate the total running time of problems with a similar level of complexity.

This process was repeated on five instances of the problems: problems with the same complexity magnitude (number of agents, parcels, and stations) but with the elements positioned differently within the scenario. This was done to palliate the irregularity among problems caused by element positioning. Averages of the

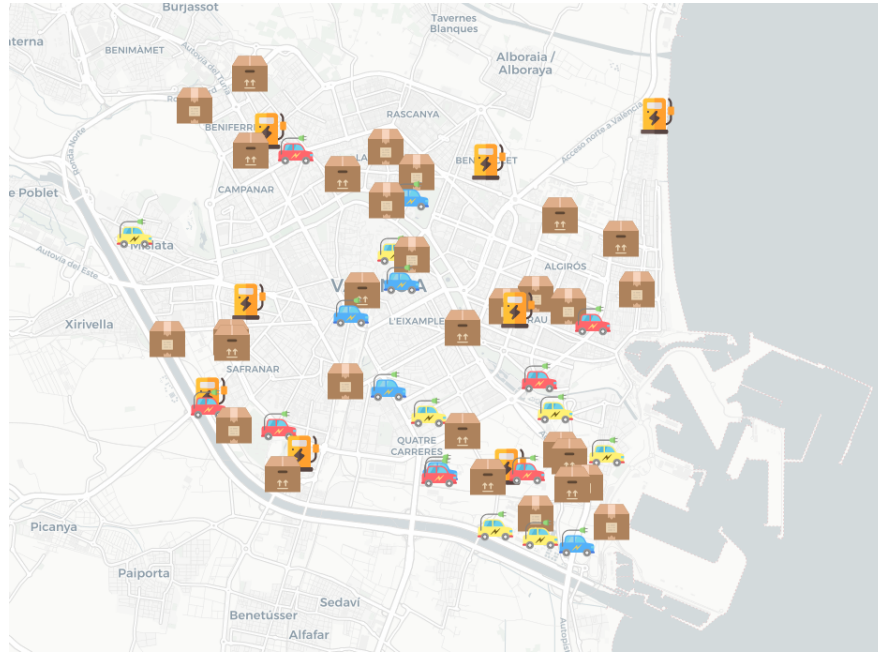


Figure 4.2: Visualisation of a problem configuration using the SimFleet software. The experimentation takes place in the main area of the city of Valencia, Spain. Different icons represent the location of electric vehicles, parcels, and charging stations.

results of the five instances are presented in Table 4.5<sup>1</sup>, where time is expressed in seconds.

As can be seen, the number of parcels per agent (P/A) is closely related to the increase in planning time. An agent with more parcels will have more ways to deliver them; thus, it will have to explore every order to find the optimal one. The standard deviation of the planning time also increases with the problem's complexity. Regarding the total time, the best-response process is expected to last longer with the more participants it has. With problems such as p500-1000, even though the P/A number is only 2, the high number of agents makes the process too time-consuming.

Even though our work focuses on our particular problem and domain, we want to compare it with a similar approach. The research in [73] approaches fleet co-

<sup>1</sup>All the tests were conducted on a single machine with an Intel Core i7-7700 CPU at 3.60GHz and 16 GB RAM.

Table 4.4: Default values of different problem variables. These variables affect the numeric value of the agent’s costs and the application of congestion.

Price per KWh	0.3 €
Power consumption per Km	0.14 KWh
Power price per Km	$0.3 \cdot 0.14$
Time penalty (waiting cost)	1
Road network cong. bound	0.3
Power network cong. bound	0.5

ordination through the so-called *Better-response* dynamics. As its name hints, such an algorithm is developed in a very similar way to best-response but with the agents proposing plans that *improve* the utility of their previously proposed plan, not necessarily being the current *best* plan. As the authors prove, the convergence to an equilibrium in such a case is guaranteed as with best-response dynamics. With this, the need for optimal planning is avoided. This enables the authors to use a general-purpose satisficing planner that can be applied to different domains. However, in contrast with our planner, the plan computation for complex scenarios is computationally more costly, as our planner is refined for the specific planning scenario. Regarding the problem modelling, we are applying the BRFP to a more realistic application using the real road network and a routing service (OSRM). In contrast, their modelling solves an electric autonomous taxi problem in simple networks with a concrete number of junctions.

Finally, assessing the experimentation results of both approaches, we can see that our system can solve scenarios with a higher level of relative complexity. The problem complexity in these scenarios depends on the number of agents to be routed and the number of junctions, increasing the planning process’s ramifications. The most complex experiments performed in [73] and [69][Section 6.4] include 6 agents (which can be interpreted as 18 since each company agent manages 3 taxis carrying customers) and between 8-12 junctions, depending on the case. Therefore, our simplest problem (p20-60) is already orders of magnitude above the aforementioned ones that require almost 1800 seconds of computation time to reach an equilibrium, which makes it unfair to compare planning and total

Table 4.5: Average performance of 5 repetitions of the problem set. Times indicated in seconds. *P/A*: parcels per agent. *iterations*: number of iterations the best-response algorithm took to converge. *total time*: time until a solution was obtained. *time/iter.* : total time/iterations. *planning time*: average time that each individual planner instance needed to return a solution.

problem	P/A	iterations	total time	time/iter.	planning time
p20-60	3	3.2	22.2	6.82	0.45±0.21
p20-80	4	3.6	72.8	20.06	1.33±0.83
p20-100	5	4.0	234.4	58.59	3.82±3.11
p50-150	3	3.4	150.1	43.61	1.12±0.60
p50-200	4	4.2	523.7	125.08	3.14±2.09
p50-250	5	5.5	2693.0	489.25	11.79±10.81
p100-200	2	3.0	206.7	68.90	0.89±0.52
p100-300	3	3.8	820.2	216.06	2.72±1.42
p100-400	4	4.8	3638.7	757.45	9.28±6.96
p150-300	2	3.0	528.7	176.24	1.53±0.92
p150-450	3	3.8	2102.2	555.08	4.73±2.47
p200-400	2	3.0	929.1	309.69	2.01±1.21
p500-1000	2	3.0	6462.8	2154.27	5.75±3.48

times directly. Our approach’s most significant benefit (with its ad-hoc planner) brings the system’s ability to manage up to 500 agents in a considerable amount of time. Nevertheless, most of our configurations reach an equilibrium in less than 15 minutes, except in the most complex cases where between 15 minutes and an hour is required, even for problems like p50-250, where the planning process is especially complex.

Our system’s major limitation comes from the complexity of planning, which is PSPACE-complete [22] or even harder in practice for optimal planning [5]. The computation time increases exponentially with the problem complexity, which means that our planner would stop returning solutions in a reasonable time for a certain number of agents or problem variability. However, given the nature of the type of problems we are dealing with, which include both the self-interest of the

agents, thus requiring a game-theoretic approach, and their planning capabilities to perform a set of tasks optimally, the theoretical complexity cannot be reduced except by improving at the practical level the computation time, as we have done using an ad-hoc planner for the restricted domain we have defined.

From the point of view of game theory, our system introduces a number of agents, which is orders of magnitude above the norm. The computation of equilibria is costly; therefore, most applications can not bear to compute them for games with such a significant number of participants. Even though our approach computes only a single equilibrium, it can do so for up to 500 participants in complex planning scenarios that feature congestion and conflicts.

### 4.7.2 Comparison of Solution Quality

Users of urban traffic systems, especially drivers, tend to act selfishly, only concerned about their goals, whether those are to reach their destination fast, follow their preferred route, etc. With the introduction of game theory techniques, we can turn selfishness into competitiveness and the latter into optimisation. If every user acts in the best way with respect to every other user in the system, their experiences will improve.

Decentralised coordination such as the one presented in this paper may seem inadequate to optimise a system globally. Nevertheless, having agents follow selfish strategies in a competitive (or non-cooperative) scenario will generally improve the agents' utilities and some of the system's metrics.

In this section, we compare the agent plans obtained by our BRFP with those obtained by a greedy strategy that aims to reproduce the behaviour of an uninformed, selfish driver. We analyse the agents' costs from a global perspective, showing that both agents' utilities and system metrics are optimised by following the BRFP. A solution with improved agent utility implies, in turn, global benefits such as optimal delivery of the parcels, both in order and time, reduced energy spending, and less resource congestion. Although there are related works such as [74] in which the quality of Nash equilibrium solutions is compared using additional criteria such as Pareto optimality or fairness, in such a case, it is necessary to list all Nash equilibria of the game, which is unfeasible in complex, realistic

scenarios such as ours. This is why we have preferred to compare with a greedy solution preserving the complexity of the scenario.

The experimentation has been carried out by obtaining solutions to the first instance of the previous 13 problems (Table 4.3). Those problems were solved using the BRFP and the so-called Greedy Solver (GS). The GS builds an agent's plan in two steps: Greedy plan-building and conflict-solving.

The greedy plan is built with the following strategy: The agent tries, at each time, to complete the delivery task whose pick-up location is the closest to its current position. If, at some point, the agent's travel capacity is not enough to complete the selected delivery task, it will instead drive to the closest station and recharge its batteries. After that, the delivery task selection will begin again. This process finishes once the agent has completed every task, thus obtaining a complete plan. Then, any action of the plan that causes a conflict with another agent is delayed until the conflict no longer exists. Ultimately, we obtain a feasible joint plan composed of individual greedy plans.

The results of this experimentation are presented in Table 4.6, where a comparison of the problems solved by the GS and the BRFP can be seen. The metrics that define the quality of a solution are the mean total cost of the delivery fleet operation (according to each agent's utility function described in Section 4.4.1); and the number of agents that experienced either a road or a power network congestion. The BRFP shows lower values for the mean total cost and the number of congested agents.

Table 4.7 further analyses the comparison by showing the percentage in which every mean cost is reduced by the BRFP (with respect to the GS's solutions). As can be seen, the average total cost is reduced between 3.23% and 10.43%. As the problem complexity increases, the reduction is higher. It can be observed how the number of parcels per agent (P/A) affects the decrease in total cost. For 2 P/A, the cost reduction does not overcome 3.81%. For 3 P/A, the reduction reaches a value of 7.81%. Finally, for problems with 4 or 5 P/A, the reduction can surpass 10%. Even though the total cost reductions are not high, there is a significant decrease in the number of congested agents (see Table 4.7, columns under "congested agents"). This shows how our approach, despite the selfish strategy of the agents, in a competitive environment can lead to socially better solutions. In problems p20-80 and p50-150, the results show an increase of agents which suffered road congestions

Table 4.6: Solution quality comparison for problems solved with the Greedy Solver and the BRFP. The problems present different values for the average total cost and the number of congested agents. The mean total costs of the fleet’s transports as well as the number of congested agents are generally lower with the BRFP

problem	P/A	Greedy Solver			BRFP		
		mean total cost	congested agents		mean total cost	congested agents	
			road	power		road	power
p20-60	3	77.07	0	0	71.45	0	0
p20-80	4	138.39	0	16	123.95	2	8
p20-100	5	200.33	0	17	182.42	0	14
p50-150	3	69.81	1	10	66.30	8	0
p50-200	4	126.96	2	27	114.65	0	14
p50-250	5	203.89	5	44	182.70	3	30
p100-200	2	30.62	0	0	29.63	0	0
p100-300	3	70.90	0	19	65.51	0	0
p100-400	4	131.03	0	70	118.10	0	38
p150-300	2	33.04	0	0	31.78	0	0
p150-450	3	72.99	0	33	67.29	0	0
p200-400	2	31.70	0	0	30.58	0	0
p500-1000	2	32.07	2	0	31.00	2	0

(values -200% and -700%) in favor of a high reduction of those that suffered power (or charge) congestions. This occurs mainly because, for this problem’s configuration, the cost increment associated with power congestion is higher than the one associated with road congestion. Consequently, when the planner only finds plans which involve either one or the other, road congestion will generally be preferred.

Ultimately, these results confirm the usefulness of our approach and show how the use of self-interested agents improves not only their benefits but brings global improvements. Our system increases customer satisfaction, reducing the time it takes to deliver all parcels. Also, the sustainability of the urban traffic system is enhanced, firstly, by reducing traffic and power congestion and, secondly, by decreasing vehicle operating times, which entails fewer kilometres travelled and, therefore, less energy consumption. In addition, this type of system also stud-

Table 4.7: Greedy Solver vs. BRFP costs reduction percentages. Columns 5 and 6 show a reduction in the number of congested agents (instead of costs).

problem	P/A	total cost	traveled kms	congested agents		waiting cost
				road	power	
p20-60	3	7.29%	4.04%	0.00%	0.00%	7.35%
p20-80	4	10.43%	3.54%	-200.00%	50.00%	10.46%
p20-100	5	8.94%	5.18%	0.00%	17.65%	8.91%
p50-150	3	5.03%	2.10%	-700.00%	100.00%	5.08%
p50-200	4	9.70%	3.43%	100.00%	48.15%	9.67%
p50-250	5	10.39%	5.51%	40.00%	31.82%	10.36%
p100-200	2	3.23%	1.48%	0.00%	0.00%	5.46%
p100-300	3	7.60%	3.70%	0.00%	100.00%	7.66%
p100-400	4	9.87%	5.44%	0.00%	45.71%	9.75%
p150-300	2	3.81%	2.59%	0.00%	0.00%	3.85%
p150-450	3	7.81%	5.06%	0.00%	100.00%	7.79%
p200-400	2	3.53%	2.00%	0.00%	0.00%	3.56%
p500-1000	2	3.34%	1.98%	0.00%	0.00%	3.39%

ies and promotes the implementation of electric vehicles as the standard in urban environments.

Ideally, we would compare our system with one that solves problems in the same domain but using a centralised approach. However, because of our ad-hoc design, there is no other application we could fairly compare it with. Even so, the relevance of our decentralised planning and the best-response algorithm is preserving the agents' private interests. No entity imposes actions on the agents; they decide for themselves their best possible actions, guided by data from the urban traffic system.

### 4.7.3 Effect of Congestion

The modelling of resource congestion and how the agents can be aware of it to avoid it gives our system the potential to test interesting scenarios. Higher con-



gestion cost increments will drive agents to avoid congestion with greater interest. In the experimentation presented so far, in Sections 4.7.1 and 4.7.2, the impact of congestion cost increments on an agent's total cost was minimal and did not strongly influence the agent's plan. In those cases, the customer's waiting time was the main parameter to optimise, as it entailed a much higher cost.

In this section, we analyse the changes in agents' costs and behaviour when *resource bounds* vary and greater *congestion costs* are introduced to the system. Therefore, for the following experiments, the power network congestion costs were multiplied by a hundred, whereas the road network congestion ones were multiplied by fifty. With this, we achieve congestion costs whose order of magnitude is comparable to the waiting cost of customers.

#### 4.7.3.1 Resource Bound Variation

For the first round of experiments, we executed problem p20-100 with values for the resource bounds ranging from 0 (any simultaneous use congests the resource) to 1 (the resource will only be congested if all agents are using it simultaneously). The relevant results are presented in Table 4.8. As can be seen, with a bound of 0, most agents get involved in congestion at some point in their plans. The number of congested agents decreases as the bound is incremented until no agent gets congested. The cost increments associated with congestion are higher according to the number of agents involved. That is reflected in both the congestion cost and the total cost, which are reduced as the bound increases and fewer agents get congested.

On the other hand, it can also be observed in Table 4.8 that there is much more congestion on the power network than on the road network when the bounds are between 0.1 and 0.25. This occurs because transports can coincide in time using the power network more easily than the roads since there is only one power network, while the roads that agents can take are less likely to coincide.

#### 4.7.3.2 Agent Behaviour Analysis

Following the trend of researching the effect of congestion, in this experiment, we analyse the change in agent behaviour (reflected in their plans) once higher conges-

Table 4.8: Average costs and congested agents variation according to resource bound. *count* columns indicate the number of agents involved in congestion. *mean* columns indicate the average cost increment and *std* columns show the standard deviation.

Power network congestion						
problem	total cost		power congestion			power bound
	mean	std	count	mean	std	
p20-100	199.7	26.3	19.0	8.1	4.4	0
p20-100	196.7	26.9	18.0	5.9	3.2	0.1
p20-100	192.1	27.0	12.8	3.4	1.2	0.25
p20-100	189.4	26.3	0.8	1.9	0.0	0.5
p20-100	188.5	26.0	0.0	0.0	0.0	>0.5

Road network congestion						
problem	total cost		road congestion			route bound
	mean	std	count	mean	std	
p20-100	207.4	29.3	20.0	15.3	7.6	0
p20-100	190.3	25.3	7.7	7.1	6.5	0.1
p20-100	186.2	25.5	0.3	0.3	0.0	0.25
p20-100	186.0	25.5	0.0	0.0	0.0	>0.25

tion costs are introduced to the system. With our base modelling, the plan building is mainly motivated by the agent's waiting cost. In other words, agents prioritize on-time delivery and thus reduce the customer's waiting time. Congestion costs may appear, and the agent will be inclined to avoid them when possible. However, when avoiding congestion involves an increase in waiting cost that overcomes the congestion cost increment, the agent will decide to assume the congestion in favor of faster delivery since it implies a lower cost.

The behaviour described above is intended and achieved thanks to the higher value of waiting costs with respect to congestion cost increments. For the following experiment, we cause a change in agent behaviour by increasing congestion costs,

making them overcome waiting costs. With this, the agent’s primary motivation will be to avoid congestion. To study such a setting, we built a small problem configuration, with 10 transport agents, 3 delivery tasks each, and 5 charging stations, all belonging to the same power network, with 2 charging poles each. The transport agents had an initial travel capacity of 20 km out of a maximum travel capacity of 30 km. Because of that, some agents will need to recharge their batteries at some point in their execution to complete their delivery tasks.

The BRFP has solved the aforementioned configuration in three different ways: (1) without considering charging congestion costs ( $w_p = 0$  in Equation 4.1), (2) with the default charging congestion cost increments ( $w_p = 1$ ), and finally, (3) with significantly higher charging congestion cost increments ( $w_p = 100$ ). The power network bound was fixed at 0.5, its default value for the previous experiments.

Our results are presented both in Table 4.9 and in Figures 4.3, 4.4, and 4.5, where the charging intervals of the agents are represented on a timeline. For simplicity, the continuous time has been discretised in the representations. Bear in mind that, as all charging stations are fed by the same power network, the specific station in which agents are charging is not relevant. Because of the same reason, any overlapping interval indicates an increment in the power demand to the power network. Power congestion will arise when such an increment exceeds the power network bound.

Table 4.9: Mean costs and congested agent number for the different executions of the problem configuration.

instance	total cost	congested agents	cong. cost	waiting cost
(1)	$71.1 \pm 16.2$	-	-	$69.9 \pm 16.0$
(2)	$71.4 \pm 16.3$	6	$0.42 \pm 0.05$	$70.0 \pm 16.0$
(3)	$74.5 \pm 18.1$	4	$3.60 \pm 0.71$	$72.0 \pm 17.7$

Comparing executions (1) (Figure 4.3) and (2) (Figure 4.4), it can be seen how the introduction of a mild congestion cost can cause some agents to opt for a plan which avoids it. In this case, agent7 moved its charge action to the beginning of its plan. With such a change, it is still available to complete every delivery task with only one charge, and, at the same time, it avoids charging in the period in which

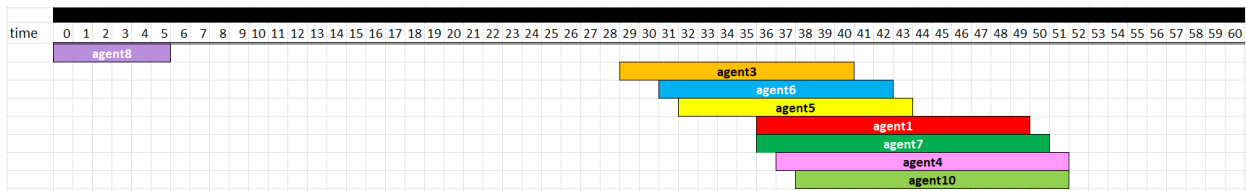


Figure 4.3: Timeline of transport agent charging intervals with no charging congestion costs. Agents are represented by coloured rectangles whose length indicates the duration of the charge. Most of the agents recharge their batteries between the 29th and the 51st time units, as they have no incentives not to overcharge the power network

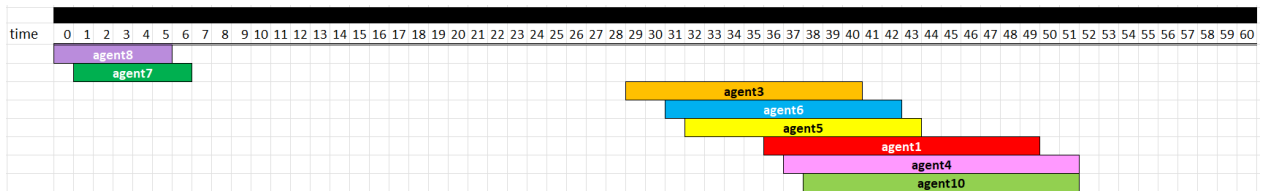


Figure 4.4: Timeline of transport agent charging intervals with default charging congestion costs. Agents are represented by coloured rectangles whose length indicates the duration of the charge. The charging congestion cost is not enough to motivate the majority of the agents not to overcharge the power network, resulting in most agents recharging between the 29th and the 51st time units

the network is overused. However, it is also clear that, for most agents, the cost increment of congestion is not high enough to induce a change of plan. Agents 1, 3, 4, 5, 6, and 10 prefer to keep their charge schedule even though all of them are affected by congestion (see instance (2) in Table 4.9), which increases the price of their charge. This is because, as we commented above, the rescheduling of their charge would entail an increment in the customer waiting time, which is the factor that contributes to the total cost the most.

With a high congestion cost increment (Figure 4.5), there is an evident change in behaviour, as agents are now interested in avoiding congestions and, in case of being unable to do so, minimising the overlap of their charge with the charge intervals of other agents. It can be seen how agent4 decides to charge two times,

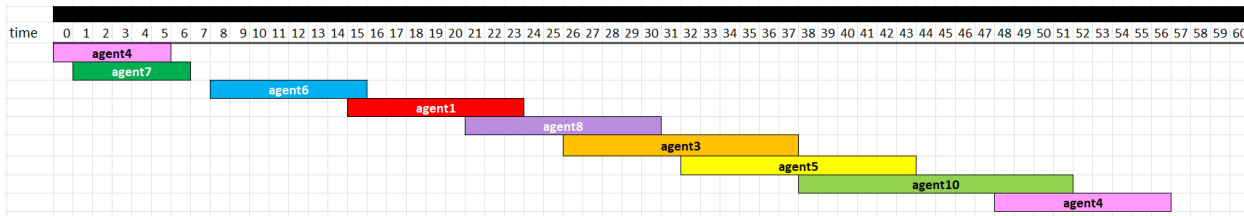


Figure 4.5: Timeline of transport agent charging intervals high charging congestion costs. Agents are represented by coloured rectangles whose length indicates the duration of the charge. The high congestion costs motivate the agents to schedule their recharge so as not to overcharge the power network, thus splitting their charging intervals uniformly over the simulation time

only to avoid congestion. Also, agent8 delays its charge, as currently charging at the start would provoke congestion with agents 4 and 7. In this case, agent8 gets involved in congestion, but it only partially overlaps with two agents (1 and 3), so the cost increment is not too high.

As it can be seen in Table 4.9, the customer waiting time slightly increases for (3), as the charge actions are now scheduled mainly to avoid congestion (in contrast with (1) and (2), in which they were scheduled to reduce waiting time). Nevertheless, the amount of congested agents is reduced by 2, and, what is more relevant, the pressure on the power network is evenly divided along with the execution of the agents' plans. Figures 4.6 and 4.7 present a visualisation of the power network usage, showing with colourised intervals concurrent charges. Darker colors indicate a higher number of overlapping charges. With the default charging congestion costs (Figure 4.6), the maximum amount of overlapping charges is 7, whereas with high congestion costs (Figure 4.7) it is only 2.

In the proposed system, a cost variation can significantly influence the agents' actions, as they are mainly motivated to reduce costs. These experiments show how the system can be tuned to achieve solutions with higher global customer satisfaction, as in (2), or reduce the simultaneous use of a resource, such as the power network, in (3).

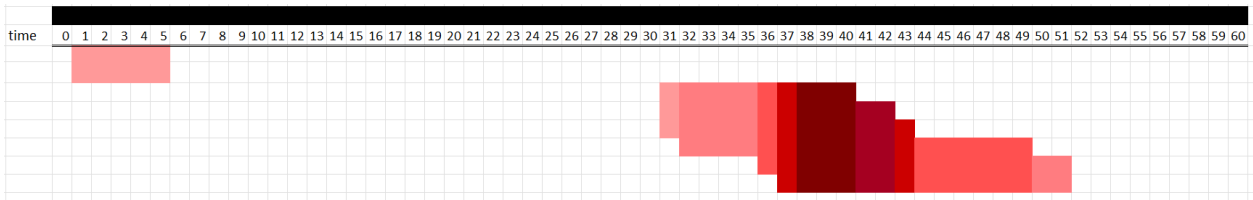


Figure 4.6: Timeline of power network usage with default charging congestion costs. Painted intervals illustrate concurrent charges. Darker colours indicate a higher number of concurrent charges. The power network is congested between the 32nd and the 51st time units, showing a major congestion between the 38th and the 40th

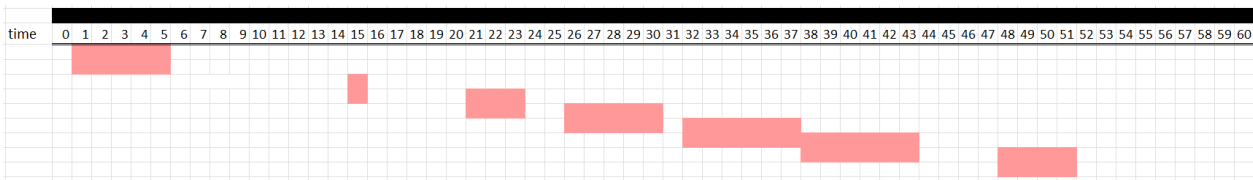


Figure 4.7: Timeline of power network usage with high charging congestion costs. Painted intervals illustrate concurrent charges. The network does not get congested, as the maximum number of concurrent charges is two

## 4.8 Discussion

This section enumerates current challenges in the field of urban transportation and optimisation. Then, it discusses the application of the described system to other smart areas and different problem domains, and describes the limitations of our system.

### 4.8.1 Urban Transportation Challenges

The research field of urban transportation and optimisation faces various challenges. One of the most prominent issues is traffic congestion, resulting from increasing urbanisation and the rising number of vehicles on the road. The adverse effects of traffic congestion include significant economic and environmental losses and a decline in the quality of life for city residents. Another challenge is to make

transportation more sustainable and reduce greenhouse gas emissions and air pollution. The development of intelligent transportation systems has led to the use of sensors, data analytics, and other technologies to optimise traffic flow and reduce congestion, but their implementation can be complex and costly. Autonomous vehicles have the potential to revolutionize urban transportation, but safety concerns, infrastructure requirements, and public acceptance present significant challenges. Lastly, the growth of e-commerce has created a major challenge for urban areas regarding last-mile delivery. Addressing these challenges and finding ways to optimise delivery routes and reduce the environmental impact of delivery vehicles is a crucial area of research in urban transportation and optimisation.

Our work addresses several of the aforementioned issues. Specifically, we contribute towards reducing traffic congestion and improving sustainability by modelling fleet coordination as a congestion game. This approach motivates each agent to optimise their use of city resources such as roads and charging stations. Our approach is also relevant to developing intelligent transportation systems, as it relies on data estimates and sensor technology to improve fleet operations and enhance the quality of life of city residents. Additionally, our coordination principles of decentralisation, privacy, and agent autonomy contribute to the development of autonomous transportation. Finally, our work is applicable to the challenge of last-mile delivery, as the domain we have developed addresses a problem within this category.

### **4.8.2 Applicability of the Proposal to Other Domains**

The main area of the city of Valencia, Spain, has been chosen to illustrate the operation of the proposed system as well as to perform its evaluation. From a general perspective, our system offers a solution for the coordination of open fleets composed of autonomous, self-interested agents, independent of the agents' goals and the concrete area where they are deployed. The coordination by means of game theory, however, requires complete information for the agents to make a strategic decision. In terms of the deployment area, this implies having access to real-time data and the computation of estimations. For the chosen domain, parcel delivery, those estimations would be traffic congestion, travelling times, and speed. Because

of that, the presented system can be applied to any smart area that fulfills its need for estimated data.

Regarding the application domain, the present work assesses traffic optimisation by coordinating open delivery fleets. For that, a so-called “ad-hoc” planner is designed, as commented in Section 4.5. The term “ad-hoc” refers to the design of the planner according to the domain; this is, according to the specific actions, conflicts and utility functions defined for the parcel delivery problem, described in Section 4.4. If we separate the system from the domain chosen in this work, it offers a general solution for coordinating autonomous self-interested agents, regardless of the agents’ concrete goals. The only essential requirement for the described system to operate is the existence of a mechanism that allows the agents to plan their actions according to their objectives, hence the creation of the ad-hoc planner. Ultimately, this implies that, with a few adjustments, it is possible to modify the presented planner, adapt it to a new domain, and thus develop a solution for that domain without changing the workflow of the entire system.

### 4.8.3 System Limitations

The described approach, despite being highly configurable, has a series of limitations that must be commented. On the one hand, the planning of agent actions is performed statically before the agents’ execution. This requires that each agent estimates their utility function. For the domain of parcel delivery, the estimation includes traffic congestion and travelling time and speed. Because of that, the most realistic application area of our system would be in a smart, highly-monitored closed area, where all components are constantly sharing data. The implementation in an open area with components or agents that are not willing to share data would worsen the estimations and, thus, the operation of the fleet.

On the other hand, the best-response coordination requires that participants are willing to share their actions with other agents. While the concrete goals may remain private, the course of action toward such goals must be disclosed. Since our system is thought to coordinate agents in a non-cooperative but non-strictly competitive scenario, some participants may have reservations about sharing their plans. However, the final objective of the coordination is the optimisation of the



whole operation and the usage of the area's resources, and thus sharing information would ultimately benefit all involved parties.

## 4.9 Conclusions

In this paper, we have presented a system for coordinating urban fleets of self-interested agents using best-response dynamics and multi-agent planning. The problem addressed has been defined as an urban mobility domain in which a set of transport agents, which may represent electric vehicles, have to carry the parcels assigned to them from an origin to their destination. To do so, each agent can strategically decide the order in which it makes the deliveries, as well as when and where to recharge the vehicle's batteries. These strategic decisions are made by each agent, in particular, depending on the strategies (plans) of the other agents to obtain the highest possible utility avoiding the congestion of both the power network and the roads, as well as conflicts due to lack of free poles in the power stations.

To resolve this mobility problem with self-interested agents, an ad-hoc planner has been developed for this domain. Each transport agent has its own instance of the planner to obtain a plan that is the best response to the plan of the other agents, i.e., the current joint plan. Thus, the resolution of the complete problem is approached by a best-response algorithm in which each agent, in turn, proposes its best plan with respect to the current joint plan. This iterative process ends when no agent changes its plan during a complete iteration, in which case, the resulting joint plan is guaranteed to be a pure-strategy Nash equilibrium.

We have tested our system's performance for different levels of complexity through extensive experimentation. Using our own ad-hoc planner is an advantage over similar systems with general-purpose planners. The optimal plans' obtention is achieved relatively quickly, even for the most complex settings. However, one must take note of the restrictions of our domain, which also help speed up the search. In addition, we have also compared the quality of the solutions obtained with our approach, which are Nash equilibria, versus solutions obtained with a greedy approach. In this sense, the solutions of our system are better (around 7% on average, and more than 10% in several cases) from a global point of view by

avoiding congestion and unnecessary waits. Moreover, being equilibrium solutions for self-interested agents, it can be ensured that none of the agents is incentivised to change its plan instead of other types of coordination solutions that agents might not respect, causing conflict situations.

Our system, because of its characteristics, is not able to adapt to new delivery tasks as fast as online approaches would. In general, any change in the initial conditions of the problem would require a new equilibrium, that is, a new execution of the best-response algorithm. However, our system would be adequate for problems in which the parcels to be delivered are not updated every few minutes since delivery windows of 15, 30, or 60 minutes could be assumed, depending on the needs. If the system were to be implemented as a smart city solution, the computing power would be much higher than that used in our tests with a conventional computer. This would imply that solutions could be computed in seconds or a few minutes.

In the future, we aim to overhaul the described system by including a mechanism that detects and deals with incorrect data estimations. One of the limitations of the system, as discussed, is the reliance on data estimates. With this improvement, we would increase system reliability for use in real-world scenarios. Also, in the line of fair and optimised coordination of vehicle fleets, we would like to explore the implementation of a task allocation algorithm that follows the principles of privacy and decentralisation established for this work. Finally, a future development of greater magnitude would be the development of a digital twin representing the deployment area of the open fleet together with its resources and with the possibility to include new and different smart services. Such work would bring a tool for significant research in smart cities and their optimisation.



# Demand-Responsive Shared Transportation: A Self-Interested Proposal

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### Abstract

*With the world population highly increasing, efficient methods of transportation are more necessary than ever. On the other hand, sharing economy must be explored and applied where possible, aiming to palliate the effects of human development on the environment. In this paper we explore demand-responsive shared transportation as a system with the potential to serve its users' displacement needs while being less polluting. In contrast with previous works, we focus on a distributed proposal that allows each vehicle to retain its private information. Our work describes a partially-dynamic system in which the vehicles are self-interested: they decide which users to serve according to the benefit it reports them. With our modelling, the system can be adapted to mobility platforms of autonomous drivers and even simulate the competition among different companies.*

## 5.1 Introduction

As the world's population increases, the scarcity of our planet's resources becomes apparent. Responsible authorities have developed a strong interest in the sustainability of our means of production as well as our way of life. Urban centres, for example, need to improve their services to make them competitive in today's world. By implementing artificial intelligence in the different systems that make up a city, it becomes a Smart City. Among the different city systems, the urban transit system stands out as one of the most complex and dynamic. However, most affordable solutions still consist of high-capacity transport with fixed routes and stops, to whose operation users have to adapt. The considerably more expensive alternatives focus on a completely individual service, which does not favour a possible reduction of greenhouse gas emissions or congestion avoidance.

In the current ever-changing dynamic ecosystem that cities define, static systems have become, if not obsolete, outdated and often uncomfortable to use. Demand-responsive transportation (DRT) systems initially served people with special needs or those who lived in rural, ill-connected areas of a city or country. This type of mobility is characterised by its flexibility to adapt to different demand patterns. At first, this meant creating routes according to the departure location of users specifically. Nowadays, however, we see some demand-responsive behaviour implemented in most current transportation services. Ranging from picking a customer up at their desired location to increasing the number of vehicles in a fleet in periods of high demand, plenty of strategies try to make the service operation reactive to the demand.

Introducing the concept of shared transportation to DRT systems, we can develop Demand-Responsive Shared Transportation (DRST). DRST services can offer a reasonable middle-point between the stiffness of public transport and the pollution and individuality of dial-a-ride services. This mobility features strategies like dynamic modification of vehicle routes and stops, on-demand creation of routes, and dynamic dispatching of vehicles according to demand. Shared mobility, however, generally involves a lower customer satisfaction with the service if compared to individual mobility. In addition, dynamic systems are complex, and their degree of dynamism affects their operation costs. DRST presents the challenge to find the balance between flexibility, shareability and sustainability of its

fleet model so that (1) the service is economically viable, (2) the quality of service is maximised and (3) the pollution derived from its operation is minimised.

Most DRST research focuses on exploring service configurations, management and operation strategies to find the equilibrium among the above-mentioned indicators. For that, it is necessary to model and parameterise the transportation system, which is generally done through either mathematical or agent-based approaches. In this work, we focus on agent-based modelling (ABM), as it allows the design of behaviours for each component of the system and the analysis of the system's operation, from which interactions and synergies may appear.

Regarding service operation, however, the reviewed publications mainly propose centralised systems. In this type of system, a central coordination entity makes all decisions, while the fleet vehicles are expected to follow every order. In practice, a manager entity accepts or rejects travel requests, assigns and modifies vehicle routes, and organises vehicles dispatching. In contrast with the centralised operation, we find decentralised systems. Decentralisation allows the decision making to be performed individually by each component of the system, taking into account that their operation must be coordinated. Given the lack of works that apply distributed techniques to their modelling, we want to explore a decentralised operation in our DRST system. Decentralisation allows for implementation with open fleets, whose number of vehicles is variable and favour the autonomy of vehicles (and drivers). Transportation services like Uber are implemented with open fleets, and their drivers can choose which requests to accept according to their own preferences. Inspired by this, we propose developing the service's operation from a distributed and self-interested perspective.

Self-interested agents (or entities) are those whose actions are guided by their own private objectives. These agents accurately represent many aspects of human behaviour, which is generally motivated by personal gains. When many of these agents operate in a shared environment (such as a city), they define a non-strictly competitive scenario. The goals of the agents may not be opposed, but their operation to reach the goals may cause conflicts with the operation of other agents. The field of game theory [138] explores the interactions among self-interested entities, offering tools to develop coordination techniques that ensure a conflictless operation. In addition, automated negotiation algorithms can also be applied for conflict resolution. Modelling with self-interested agents allows us to reproduce a

DRST system where vehicles of different enterprises may “compete” to serve the customers of one mobility platform. We believe such a competition may result in a better quality of service for the user and higher adaptability of the system to the demand.

We hope to open a discussion on distributed demand-responsive shared mobility with this work. The aim is to analyse and discuss the requirements a DRST system needs if its fleet is implemented by self-interested vehicles. In accordance with the above, we propose a system architecture for a partially-dynamic system that accepts real-time travel requests as well as bookings. We discuss the particularities that a fleet of self-interested vehicles involves and describe how the assignment of bookings and requests works in our distributed paradigm.

The rest of the paper is structured as follows. Section 5.2 discusses relevant works in the field of DRT systems, focusing on the differences in configuration and modelling approaches. Section 5.3 presents an overview of the proposed system, briefly describing our modelling and the system’s architecture. Section 5.4 discusses the operation of the static subsystem of our proposal, which takes care of booked trips. Section 5.5 describes how our system deals with real-time travel requests. In Section 5.6 our proposal is analysed and compared to other works. Finally, Section 5.7 assesses our work and comments on future extensions.

## 5.2 Related Work

Among the many works that explore DRST systems, three research currents stand out: service impact and viability assessment, system modelling, and operational strategy optimisation. The current proposal lies between the last two, which are generally addressed together in scientific papers. In this section, we discuss different contributions to the field of demand-responsive mobility, grouping them according to the previously mentioned research currents.

There has been extensive research on the topic in hand, starting around the ’90s, when flexible transportation was aimed at disabled people [108] Later, it evolved into a kind of public transport operated in zones with a low population density or low demand. Nowadays, it is being considered a potential mode of transportation for the general public, although its usefulness with respect to traditional transporta-

tion alternatives is yet to be demonstrated. Many recent works focus on the impact assessment and economic viability of DRST services. This type of research does not focus on algorithms or optimisation. Nevertheless, it is an essential part of mobility research, as it deals with transportation policies and user behaviour. As it is common in transportation research, most of these works are focused on particular cities or rural areas whose population lacks efficient mobility services. Alternatively, some authors propose using DRST services to substitute unproductive and ill-suited traditional transportation methods. The work in [20], for instance, proposes the replacement of the bus service in the city of Velenje (Slovenia) with a combination of bike-sharing and DRT systems. Their cost analysis reveals that the new system would not incur a much higher cost for the municipality while covering the citizen's displacement needs much better than the current service.

A very relevant study for our particular modelling of DRST is the work in [135], where authors assess the implementation of an autonomous DRST service that communicates the rural area surrounding the city of Bremerhaven (Germany) with its city centre. Through multi-agent simulation, the authors find that operational and environmental costs significantly decrease if the individual transportation vehicles are entirely substituted with a fully automated DRT service. Their conclusions, however, remark how a fully autonomous operation of vehicles is crucial for the economic viability of the service. Cutting operator (driver) costs is essential to offer a competitive and attractive price policy. Our proposal bears this in mind and, although it could be applied to human-driven vehicles, the coordination methods we explore can be employed by autonomous vehicles once technological advances allow their implementation.

The interest in demand-responsive transportation also comes from its inherent sharing economic model. In a sharing economy, goods and resources are collaboratively shared by individuals and groups. From a general perspective, the sharing economy can reduce resource consumption. Focused on transportation systems, it can improve their sustainability by reducing, for instance, carbon dioxide emissions. In this regard, authors in [51] present a hybrid unsupervised learning model which categorises taxis according to many features that are related to their CO<sub>2</sub> emissions. Their model proves useful to cluster vehicles with similar degrees of emissions and identify the most polluting ones for further improvements.

Reviewing the literature, we identified a set of elements which are common



among all DRT systems (routes, stops, and driver strategy, among others), although the use of these is highly configurable, varying in each specific system. Table 5.1 enumerates the observed configurations. Such a variety of options presents advantages and disadvantages. On the one hand, a concrete system can be adapted to fit the mobility needs of a specific community or group of users. Many strategies can be followed, whether through flexible routes and stops, allowing reservations, changing timetables, or more.

On the other hand, high flexibility in configuration can lead to a more costly implementation. In addition, in terms of research, each particular work focuses on a specific system configuration and characteristics. This may result in the type of DRST system that a transport manager is interested in not being sufficiently researched to be adequately implemented.

As commented in the introduction, many works focus on the research of management strategies and fleet operations that permit an economically viable, sustainable and reliable service [84]. These indicators must be defined according to the concrete service being researched. The balance among the indicators is generally found through experimentation with different system configurations. Besides this, an appropriate approach to model the system must be chosen. The most popular approaches for the topic at hand are either mathematical or agent-based, being the latter generally coupled with simulation. Following, we comment on relevant works which present the characteristics stated above.

The work in [7] models the dynamics of a DRT system mathematically and aims to identify a management strategy that incentivises system users to adapt the timing of trip requests uniformly over time. At the operational level, three strategies are identified concerning the pickup and dropoff of users: (1) minimise total distance travelled by finding the next closest pickup/destination point at each stop; (2) Alternate between pickup and dropoff phases (of  $n$  customers each), reducing travel time variance; and (3) Each pickup is followed by the nearest unloading and vice versa. The total system cost is estimated according to the operational capacity of the system and the number of requests waiting to be served. Finally, it is a linear combination of the number of vehicles, driver salaries, and energy and maintenance costs. The distinguishing feature of this work is that it studies the saturated system, with a number of waiting requests higher than the system's operational capacity. The authors then aim to find an equilibrium among customers

Table 5.1: Review of DRT system configurations. Column headers identify common elements to all systems. Rows enumerate configuration options of their corresponding element. Read from top to bottom, the options transition from a non-flexible shareable system to a flexible but less shareable system.

<b>Stops</b>	<b>Routes</b>	<b>Fleet</b>
Fixed	Fixed	Cooperative
Flexible	Flexible	Decentralised
On-demand	Hybrid	
	On-demand	

<b>Vehicle capacity</b>	<b>Services</b>	<b>Dispatching</b>
+20 passengers	Trip reservation	All vehicles available
8-20 passengers	Real-time requests	Dynamic
4-8 passengers	Hybrid	
1-4 passengers		

from the congestion theory point of view. A dynamic pricing policy is applied to motivate the users to advance or delay their requests to reduce their prices.

In contrast with the previous, the work in [64] uses ABM to describe a DRST system with fixed and flexible routes and stops. The authors aim is to analyse the necessary trade-off among the system’s economic efficiency , the service quality and the fleet’s sustainability . Their experimentation is performed with the NetLogo<sup>1</sup> simulator and based in a real-world setting. Different system configurations are tested, including fleet size, vehicle capacity, and dispatching strategies. The results present a specific system configuration that guarantees the system’s economic viability while improving its sustainability with respect to a taxi service, although this inevitably comes at the cost of a reasonable reduction in service quality. Balancing the metrics above proves to be a challenge in any DRST research.

In line with the functional design of DRST systems, authors in [63] extend their previous work to compare, through multi-agent simulation, their system with a traditional taxi service. They define three indicators: transport intensity, related to operational costs and environmental impacts; total unit cost, which represents

<sup>1</sup><https://ccl.northwestern.edu/netlogo/>

the total costs of the system; and effectiveness in terms of satisfied customers. The system was measured by varying the number of vehicles and their capacity. Their results point out how in low demand conditions, the taxi service outperforms DRST. On the contrary, during periods of high demand, the higher capacity of shared vehicles enables the demand-responsive service to stand out. Nevertheless, their analyses are inconclusive for medium demand intervals.

Also within the operational strategy of a DRT system, one must decide the dynamism of its operation. Given the demand-responsive feature of this service, most works (including the last two mentioned) present fully dynamic systems, where the demand is unknown, and the requests are dealt with in real-time. In contrast, authors in [158] model a service with degree of dynamism. Compared to fully dynamic systems, theirs accepts bookings, which are requests that are known before time. A request is defined by pickup and destination locations and a time window describing the acceptable times for the client to be picked up and dropped off. Their system works in two steps. First, all the static requests are divided among the fleet's vehicles, creating an initial routing for the day. Then, as the fleet operates, dynamic requests appear. These requests are assigned to a vehicle ensuring minimal cost increments and respecting time window restrictions of the already assigned requests. If no vehicle is fit to serve the request, a new vehicle is dispatched, or the request is rejected. The conclusions drawn from this paper indicate that a dispatching system incurs higher system costs and serves fewer requests when the request arrival is partially dynamic, compared to static or fully dynamic operations.

In this paper, we model a system that is inspired in the revisited works. Nevertheless, we introduce two features that suppose a new approach to demand-responsive transportation.

On the one hand, we want to explore the potential of shared demand-responsive transportation. Shared transportation [142] consists of reducing the number of vehicles in a transport system by grouping different passengers, initially not related to each other, in vehicles with a capacity for two or more users. Generally, passengers are grouped so that the vehicle route can meet their transportation needs (regarding time and location). Therefore, passengers with origin and destination locations close to each other or whose origin or destination points are on the route to another passenger will be grouped together. Shared mobility has the potential

to favour sustainability in transport systems by reducing the number of operating vehicles. However, it can also lead to a reduction in user satisfaction [107, 81], because as the system becomes more shareable, it also becomes less flexible and adaptive to the different transportation requests of each individual user.

On the other hand, we want to develop a decentralised system, which includes the possibility for different transportation companies to serve the same demand. Most of the works that research demand-responsive transportation describe centralised systems, where a manager entity has full control over the vehicle fleet. The dispatching of vehicles, acceptance and assignation of transportation requests, and vehicle routing are all decided by the system. Although some centralised systems include compensations for drivers forced to change their routes in real-time [17], most assume that drivers will act according to the orders of the central entity. In contrast to this, our system will model vehicles as self-interested agents, which act according to their own private interests. The transports in our system will have the chance to accept or reject requests and even alter their routes according to the benefits or costs that these changes would imply for themselves. Consequently with the stated above, the fleet of our system can be implemented by either fully autonomous or human-driven vehicles.

According to [92], a taxonomy on the coordination of autonomous vehicles, with our self-interested modelling of vehicles, we need to apply agreement or negotiation approaches to sort out the operation of the fleet. Therefore, we propose game-theoretic and automated negotiation techniques [133]. Modelling with self-interested agents allows us to reproduce a competition among drivers of different companies. These drivers, although mainly interested in their own benefit, are also keen to coordinate with potential competitors to optimise both their own operation and the operation of the global mobility system.

Following, we describe our system's particularities, present its infrastructure and discuss its operation.

## **5.3 Overview**

From a general perspective, a demand-responsive transportation system works as follows: users issue a travel request indicating the location and time they want to

be picked up and their desired destination. Then, the fleet manager chooses a vehicle, among the available, to serve the customer request. This involves driving to the customer's location, picking them up and dropping them off at their destination. All of this has to be performed considering any possible time restrictions of the customer's request (pickup time, maximum arrival time). The assignment of requests to certain vehicles is performed in a centralised manner, aiming to maximise both the system profits and customer satisfaction. For this, routing and scheduling algorithms compute the best global assignment each time a travel request arrives. This computation may result in one or many vehicles having to dynamically change their own route to attend to the new requests they have been assigned. With a centralised system, however, it is assumed that all vehicles will be willing to adopt those changes, as they have no real willpower.

In contrast with the stated above, our proposal consists of a partially-dynamic demand-responsive transportation system that makes use of autonomous (in terms of will) shared vehicles to serve its users. Our system focuses on the decentralisation of the service and the self-interest of the system's vehicles. This type of autonomous vehicle has its own private goals and keeps its information (and its customers' information) private. With this modelling, we can have a system that serves customers from different mobility platforms or companies. Therefore, the vehicle fleet of the system shares properties with open fleets. The total number of vehicles may vary, and each individual vehicle acts as an autonomous entity. The goal of the fleet is to serve as many travel requests as possible, maximising customer satisfaction while minimising overall costs. This goal, however, is achieved through the self-interested behaviour of the vehicles, which aim to maximise its own benefits, thus also reducing costs. Similarly to customers, the fleet may be integrated with vehicles from different companies. To make the system suitable for shared mobility, we assume that vehicles have a capacity that ranges from four to eight customers.

Although the utility that serving a customer request reports to each vehicle is private, there are a series of shared elements among all vehicle fleets. The vehicles have routing and scheduling algorithms that enable them to plan their operation according to their assigned tasks and time windows. In addition, a traffic condition estimator is available for all vehicles so that they estimate, to some extent, the time that will require serving a concrete travel request. The information retrieved by

such a system is the same for every vehicle.

The crucial difference with respect to a centralised system is that self-interested vehicles have the will to decide whether to serve a travel request is in their best interest or not (if it reports them more benefits than costs). In addition, travel bookings and requests in our system are visible to every vehicle. One or more vehicles may be interested in serving a concrete request, making it necessary to introduce distributed processes to decide which vehicle is assigned the disputed request. This creates a somewhat competitive scenario among the fleet vehicles. Each request will have a different “value” to each vehicle, as they have their own utility function. Because of that, requests will generally be assigned to the vehicle which is more interested in it (the one to which the request has more value). We propose the use of Best-response dynamics and auction procedures to sort out the request assignments. Both these methods are detailed below, in Sections 5.4.1 and 5.4.2 respectively. The aforementioned techniques are concrete proposals, and they must be understood only as such. There are a variety of processes that could be employed for the task at hand, which would have to be tested to select the most appropriate.

As we mentioned above, we model a partially-dynamic system. This means that the travel requests our system accepts are of one of two types: bookings (static) or real-time (dynamic) requests. Figure 5.1 shows the system’s architecture, which is split into two parts: *static* and *dynamic*.

The static part deals with travel bookings; displacement requests which are known before time. The static subsystem can be run every day or every few hours to obtain a route planning for every fleet vehicle, allocating the bookings in a distributed, self-interest guided manner. All fleet vehicles have a maximum number of bookings that can serve during a concrete working period. Such a number is proportional to the duration of the working period. The static subsystem is described in detail in Section 5.4.

The dynamic subsystem takes care of real-time requests, which arrive while the fleet is already operating. These requests may ask for the fastest possible pickup, in contrast with programmed pickups. The vehicles are filtered to sort out which of them can get a real-time request assigned. . Any vehicle which, to include the new request in their route, fails to preserve the time restrictions of its previously accepted requests, will be discarded from the assignment process. Then, the dis-

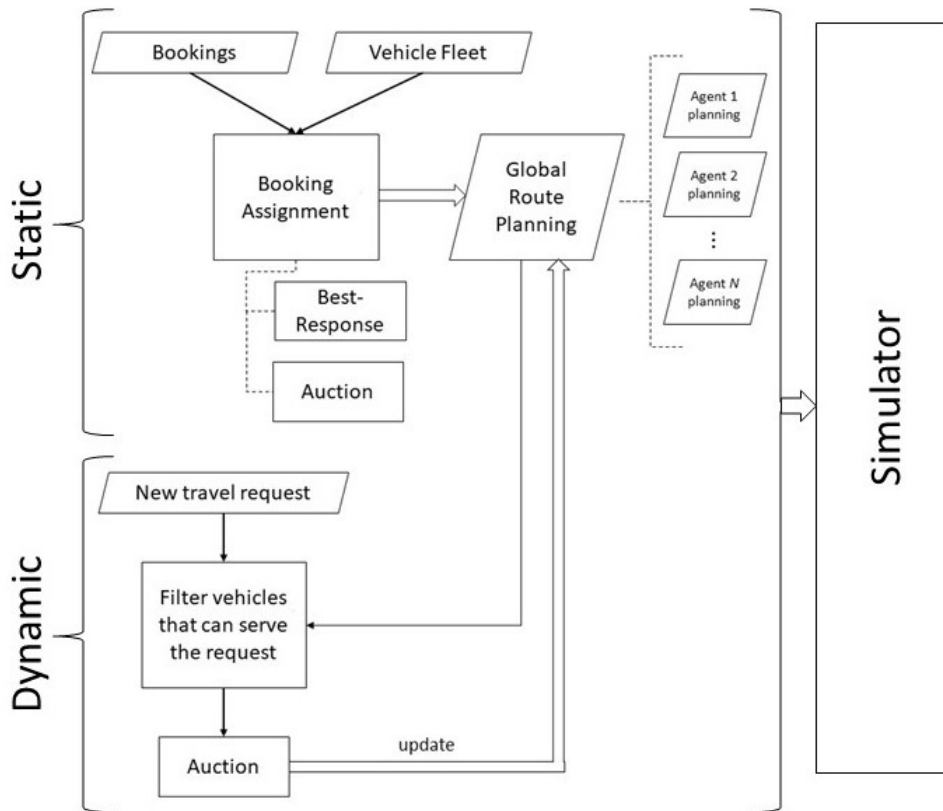


Figure 5.1: System architecture, split into a static and a dynamic subsystem. The proposed architecture may be communicated to a simulator which allows for system testing, tuning and visualisation.

tributed process takes place among the leftover vehicles through an auction. The vehicle that gets the request assigned updates its route planning accordingly to serve it. The dynamic subsystem is described in detail in Section 5.5.

Finally, we propose the integration of the proposal with a simulator. A simulator would enable the system's managers to test the system with different configurations of vehicles, vehicle capacity and customer demand. In addition, it can be used to tune the parameters of the different algorithms and find the best combination. Specifically, we would integrate our system with SimFleet [117], a multi-agent based simulator that counts with a web interface that allows the visualisation of the system in operation.

Following, we detail each part of our proposal, characterising the format of

bookings and travel requests and describing the distributed assignment processes that take place among the self-interested vehicles.

## 5.4 Static Subsystem

The static part of our system computes an initial route planning for every fleet vehicle to perform during the following working day or period (as it could be run to plan for periods of a concrete number of hours). In order to do so, it receives a set of client *bookings*, as well as the set of vehicles that will be available during the day.

A booking  $b$  is defined in our system as a tuple with the following parameters:

$$(5.1) \quad b = \{L_{pickup}^b, L_{dest}^b, T_{pickup}^b, T_{dest}^b, T_{thresh}^b\}$$

- $L_{pickup}^b$ : **Pickup location** where the user issuing the booking will wait to be picked up by a vehicle.
- $L_{dest}^b$ : **Destination location** where the user issuing the booking wants to be dropped off the vehicle.
- $T_{pickup}^b$ : **Preferred pickup time** at which the user expects to start travelling towards its destination.
- $T_{dest}^b$ : **Preferred arrival time** at which the user expects to be dropped off at its destination. The system will indicate a minimum arrival time according to the expected pickup time, trip distance, route, and predicted traffic flow. The user is free to delay its preferred arrival time, which would give the system more flexibility to allocate their trip.
- $T_{thresh}^b$ : **Time threshold** indicating the amount of time the user is willing to wait past their preferred pickup time or the delay on their preferred arrival time they could accept. A longer time threshold would give benefits for the user, such as a lower service price. It is crucial to incentivise the duration of



this parameter as it offers the vehicles more free time to either better adjust their routes or serve incoming real-time requests.

According to the definition of a booking, the utility that serving a booking  $b$  reports to a vehicle  $v$  is defined by Equation 5.2. Let  $dist(x,y)$  be a function that returns the distance travelled by road between locations  $x$  and  $y$ ; and  $service\_fare(time)$  a function that returns a price value according to the  $time$  passed to it. Let  $v_{loc}$  be the current location of  $v$ ;  $km\_price$  a fixed price per trip kilometer;  $w_{thresh}^v$  a weight that determines the importance of a flexible threshold for  $v$ ; and  $L_{pickup}^{b+1}$  the pickup location of the booking  $b+1$  that will be served after  $b$ .

$$(5.2) \quad Utility(b, v) = benefits(b, v) - costs(b, v)$$

The benefits (Equation 5.3) that serving booking  $b$  reports to a vehicle  $v$  are determined by the distance travelled by the user that issued the booking, the time in which the booking time window begins and the time threshold, whose influence is pondered by a weight. A service that begins at a specific time of the working period might be more costly for the customer. Ideally, this would, to some extent, motivate users to spread their trip times uniformly throughout the working period. In addition, the time threshold represents more benefit for the vehicles the longer it lasts, as it gives them more free time to adjust their route or serve real-time requests.

$$(5.3) \quad \begin{aligned} benefits(b, v) = & dist(L_{pickup}^b, L_{dest}^b) * km\_price + \\ & service\_fare(T_{pickup}^b) + T_{thresh}^b * w_{thresh}^v \end{aligned}$$

As for the costs (Equation 5.4), these include the distance travelled while the vehicle is empty and the inverse of the time threshold. With this, trips that start nearby the vehicle and finish nearby another assigned booking will be more attractive. The threshold, in this case, adds fewer costs the longer it lasts.

$$(5.4) \quad costs(b, v) = dist(v_{loc}, L_{pickup}^b) + dist(L_{dest}^b, L_{pickup}^{b+1}) + \frac{1}{T_{thresh}^b * w_{thresh}^v}$$

As it can be seen, the functions combine values with different units. For a correct utility computation, those values would be normalised to adjust their magnitudes. In addition, take into consideration that these are equations developed for the current proposal. They could be modified in the future and adjusted to other system configurations.

Once all the information has been loaded, a distributed process begins in which the fleet vehicles, all modelled as self-interested agents, build their routes by choosing to serve one booking at a time, taking turns. As they incrementally build their route planning, the vehicles take into account the time restrictions associated with every booking in order to ensure all clients will be served satisfactorily. Vehicles run a routing algorithm that analyses the inclusion of the next booking they are interested in serving into their current route. A vehicle will be able to choose a booking if its inclusion in their route planning does not delay any of the already selected bookings past their threshold.

Regarding the distributed booking allocation process, we propose two alternatives in which the decision to include or not a booking in their routing plan is driven by the self-interest of each agent. In particular, we discuss a game-theoretic approach named Best-response coordination (Section 5.4.1), in which the vehicles, in turns, select the booking that better fits their routing, also taking into account the routing of every other participant vehicle. This process eventually converges to an equilibrium, an assignment of bookings to vehicles from which no vehicle is incentivized to deviate. On the other hand, we propose an approach based on automated negotiation: the Bertsekas auction algorithm (Section 5.4.2). This algorithm allows vehicles to bet on the bookings they are most interested in.

Finally, as an extra feature of our system, we enable users to configure periodic bookings. A periodic booking is issued with the same parameters regarding location and daytime, but with a different date. A clear example of a periodic booking would be one which is repeated from Monday to Friday to transport a user from their home to their workplace (or vice versa). Periodic bookings are comfortable for our system and would be encouraged among users, as they provide certainty for the initial route plannings of each vehicle for each working period.

### 5.4.1 Best-response Coordination

The best-response coordination [68, 73] is a game-theoretic distributed algorithm which obtains an equilibrium among the strategies of a set of agents. In game theory, an equilibrium is a solution or set of agent actions from which no agent is incentivised to deviate. In other words, every agent has decided on a set of actions that reports them the maximum possible benefit with respect to the actions of every other participant agent. Applying this concept to our DRST system, with an equilibrium we obtain a coordinated global route planning; that is, a route planning containing the individual route plannings of every vehicle. The booking assignment of the global route planning creates no conflict during the vehicles' operation.

To apply such an algorithm would require the definition of the booking assignment as a multi-agent planning task. Therefore, the route planning that each vehicle intends to perform during its operation would be encoded in an agent plan. An agent plan, in this context, would describe the bookings the vehicle would like to serve, indicating also the route and schedule it would follow. During the best-response process, the agents propose their best plan (the one that reports them more benefits), taking turns. After a whole round, the agents reevaluate the plan they proposed taking into account the plan of every other agent. If the actions of another agent are in conflict with theirs (for instance, because more than one agent is interested in serving the same booking), the agent will propose a different plan which (1) avoids any conflict, and (2) is its current best plan. This process repeats iteratively until no agent has modified its plan after a whole round. This means that each agent is proposing their best plan with respect to every other agent's best plan. Consequently, as no agent will benefit from switching plans, an equilibrium has been reached. The agents are coordinated, no conflicts will arise from the execution of their plans, and their private interests have been preserved.

This coordination, however, needs vehicle information to be shared among participants. As commented above, agents propose their best plan with respect to other agents' best plans. This implies that every agent has complete information about every other agents' intentions. In addition, when a booking conflict arises (more than one vehicle interested in serving the same booking), information such as the location of vehicles is vital to determine who will end up serving the book-

ing, as generally a vehicle closer to it will be able to get there sooner, increasing customer’s satisfaction and reducing wasted time.

### 5.4.2 Bertsekas Auction

The Bertsekas’s Auction algorithm, presented in [15], is generally used to assign a set of jobs (or persons) to a set of tasks (or objects) such that each job is assigned to only one task and the effectiveness of the assignment is optimised. We adapted the formulation of this distributed algorithm to our problem modelling. Following, we describe the algorithm’s input and its operation.

For our proposal, we have a set of  $m$  bookings which must be assigned to one of the  $n$  vehicles of the fleet. Each booking  $b_i, i \in [1, m]$ , has a real static cost  $price(b_i)$  associated to it. This cost is independent of the vehicle serving the booking and is computed only taking into account the attributes of the booking (distance between pickup and destination, time of pickup and flexibility on the time threshold). In addition, for each vehicle  $a_j, j \in [1, n]$ , each booking has a unique estimated cost  $estim(a_j, b_i)$ .

The estimated cost of each booking for a particular vehicle is determined by the costs that would imply to serve such a booking if it was assigned to it. Its value depends on many factors such as the vehicle’s location, the number of bookings it has already assigned and the necessary modifications in its route planning to serve the new booking. Because of that, the estimated cost that each request has for every vehicle is unique. This estimated value will determine the vehicle’s willingness to serve a particular booking.

Given the aforementioned input, the algorithm develops in iterations until each booking is assigned to a vehicle. An iteration works as follows: The vehicles compute their own perceived cost for each booking,  $cost_{a_j}(b_i)$ , by adding the estimated (unique) and real (static) costs:

$$(5.5) \quad cost_{a_j}(b_i) = estim(a_j, b_i) + price(b_i)$$

Each vehicle bids on the booking with less cost:  $min(cost_{a_j}(b_i))$ . The “price” of the bidding is the difference between the cost of the booking with the second lowest cost ( $b_{sub}$ ) and the one with minimum cost ( $b_{min}$ ):

$$(5.6) \quad bid_{a_j} = cost_{a_j}(b_{sub}) - cost_{a_j}(b_{min}).$$

Each booking that has received at least one bidding is assigned to the highest bidder. Then, the real cost of such a booking is incremented by adding the highest bidding price to it. Let  $a_u$  be the vehicle with the highest bid ( $bid_{a_u}$ ) for booking  $b_i$  and  $price'(b_i)$  be  $b_i$ 's price for the next iteration:

$$(5.7) \quad price'(b_i) = price(b_i) + bid_{a_u}$$

With this price increment, the algorithm makes all other vehicles bidding for booking  $b_i$  aware of how interested is  $a_u$  in it. If the increment in the real price does not dissuade other vehicles from bidding for  $b_i$  in the following iteration,  $a_u$  could lose it (get the booking unassigned). At the end of the process, each task will be assigned to the vehicle that can afford to “pay” more for it. In other words, the vehicle that is willing to increase its costs the most to serve the booking's customer.

Our system will generally receive a higher number of bookings than the number of vehicles in the fleet. Therefore, to assign all of them to the different vehicles, we must run the auction algorithm iteratively. At the end of the first iteration, the vehicles will have one booking assigned to them. Each consecutive iteration, they may be assigned one more booking. As explained in Section 5.3, the vehicles have a limit in the number of tasks they can be assigned during a specific working period, whether it is the whole working day or a few working hours. Once a vehicle reaches that limit, it will not participate in any following auction. Finally, when every booking has been assigned, the iterative auctions finish. At that time, each vehicle counts with its own individual route planning, which, as every booking is assigned to a single vehicle, will not cause any conflicts during the operation.

## 5.5 Dynamic Subsystem

The dynamic side of our system deals with real-time (or online) travel requests. This type of request share the attributes of a booking (Section 5.4); although its  $T_{pickup}^b$  can be configured as “as soon as possible”. Real-time requests are issued

by system users through the application and arrive at a pool of requests that is visible to every vehicle. Once again, the decision to serve a request of the pool is based on each individual vehicle's self-interest, taking into account the necessary restrictions. The utility that serving a real-time request reports to a vehicle is computed in the same way a booking's utility (see Equations 5.2, 5.3, and 5.4 in Section 5.4).

The inclusion of an online request in the route planning of a vehicle implies new scheduling of the already accepted trips. In addition, this rescheduling is performed while the vehicle is most likely already serving one of their bookings. Therefore, such inclusion must not delay any of its already assigned requests or bookings past their threshold. When a new travel request is issued, the first step is to select as potential servers the vehicles that can add it to their route planning while respecting the time restrictions of their other bookings. For this, every vehicle in the fleet calculates a new scheduling that includes the new request. If the scheduling can not be computed, the vehicle will not be able to show interest in serving the request.

The assignment of the new request is done among the vehicles that passed the previous step. The computation of their new schedules gives the vehicles the information that defines how interested they are in serving the request, i.e., the expected benefit obtained from serving it. A distributed process takes place in which the interested vehicles bid for the request to decide who will serve it. The request will be assigned to the auction winner, who will update its schedule to the one it computed before. The time differences among schedules are informed to the corresponding users through the application. Similarly, the user that issued the new request will be informed of their expected pickup time.

Considering that new travel requests may appear at any time, the vehicles adapt their operation to maximise the number of requests they can serve. In this regard, the time between consecutive bookings or requests can be administered by each vehicle according to different waiting strategies [166]. If the *Drive first* strategy is followed, the vehicle will depart towards its following location immediately after the current request is served. In contrast, the *Wait first* strategy favours waiting for the longest possible time in the current location as long as the time restrictions of the following requests are preserved. Finally, the *Modified dynamic wait* consists in waiting at the current location for a concrete time, aiming to arrive at the location of the following request precisely at the beginning of its time window so that the

customer is served without waiting. In our system, each vehicle could employ its preferred waiting strategy.

## 5.6 Discussion

Throughout this work, we have discussed the many configurations that demand-responsive mobility can have. From all those, our system is modelled with fully-flexible routes, on-demand stops, a decentralised fleet of self-interested vehicles, having each vehicle capacity to carry four to eight passengers, and offering trip reservations as well as real-time travel requests. The service we propose does not differ that much from on-demand transportation services like those of Uber or Cabify. However, from the shareability perspective, our system improves on traditional alternatives, although it can not be compared to public transport services. Regarding sustainability, the type of service we offer has the potential to reduce private vehicle usage in favour of shared vehicles [135]. Such a potential is increased if we consider the vehicles could run on electric power, thus avoiding carbon dioxide emissions during their operation. To draw any concrete conclusions, however, we need to gather specific data about our proposed fleet's sustainability. We plan on doing this in the future by simulating the system and experimenting with different fleet sizes and vehicle capacities.

In terms of our proposal, the self-interest of the vehicles is defined in their utility function. The utility that serving a certain booking/request returns is equal to the benefit it produces minus the cost it involves. In turn, benefits relate to the distance travelled while the customer is on the vehicle, while costs derive from vehicle maintenance and empty movements, among others. With this modelling, certain requests may be unattractive to every transport of the fleet. Requests whose pickup or destination location are far away from any vehicle may be at risk of reporting more costs than benefits. To tackle this problem, we can follow many strategies.

On the one hand, we could incentivise the vehicles to serve unattractive requests by increasing their benefits. This, however, may involve an increment on the prices the user has to pay to be served, which would potentially impact negatively on customer satisfaction. On the other hand, the vehicles might be forced to

serve unattractive requests and later compensated. Possible compensations would be an increment on their benefits or, for instance, advantages during the distributed booking/request assignment processes. There is, of course, a third option which consists of enabling the system to reject unassigned requests. If after the assignment processes no vehicle has shown interest in a particular request, the issuing user would be informed, through the application, that the system can not serve them at the moment. This feature is currently implemented in most traditional transportation systems, which negate service if their operative capacity has been reached. This measure may worsen quality of service but reduce, at the same time, operational costs, as seen in [158]. To correctly assess the impact of this measure on our proposed system, however, we need experimentation.

Most of the reviewed literature points out the difficulty to have flexible transportation with a profitable operation. According to many works, the more flexible and responsive a system is, the higher tend to be its operation costs. It can therefore be inferred that in a system with the features we propose achieving economic viability of the service might be challenging. Although the current work is in an early stage, it is interesting to analyse the requirements to implement our proposal in a real setting. In that regard, our system may need some type of public subsidy to have an adequate quality. With that, users would pay lower prices for the services, which would motivate other users to make use of our system instead of a private vehicle or other less sustainable alternatives.

## **5.7 Conclusions**

In this work, we have explored the particularities of Demand-Responsive Shared Transportation systems. Our contribution consists of a proposal for a partially-dynamic system whose fleet is implemented by self-interested vehicles. On the one hand, our system can deal with trip reservations through its static subsystem and real-time travel requests through its dynamic part. On the other hand, using a distributed fleet enables private information to be retained and optimises service quality through vehicle competition. With our approach, the need for a central coordination entity that gives orders to the fleet is avoided. Finally, we propose the integration with the SimFleet simulator to set up and execute experiments.



Regarding the specific configuration of our DRST system, we model a fully-responsive service with on-demand routes and stops. Nevertheless, we do not limit ourselves to this configuration and are eager to design and test others in the future. For the current work, we chose to focus the discussion on the differences among fully and partially-dynamic systems, decentralisation of the fleet and the modelling with self-interested vehicles.

In contrast with the reviewed work, our proposal defines a decentralised operation of the system. In addition, we use self-interested agents to model autonomous vehicles or drivers. The use of self-interested agents supposes a novel approach in transportation modelling, where vehicles are generally assumed to follow orders of a manager entity. With them, we can reproduce an open fleet, a new approach to DRST systems. Our setup gives us the chance to explore the application of distributed techniques, such as the best-response algorithm or the Bertsekas auction algorithm, to coordinate the fleet's operation. These techniques ensure that vehicles (or drivers) serve transportation requests according to their own interests. Furthermore, we could reproduce a system in which vehicles of different companies compete by serving clients of a single transportation platform. By introducing decentralised self-interested operation, we hope to improve both the vehicle's benefits and the client's satisfaction.

The natural future step for this proposal would be an implementation of the infrastructure. Concretely, we plan to: (1) specify the modelling refining the formulas for the costs, benefits and utility of the vehicles. In addition, define system performance indicators regarding economic viability, service quality and sustainability. (2) Implement and test the described system, assessing the use of the proposed distributed algorithms and testing also alternative ones. Finally, (3) overhaul the SimFleet simulator to enable the creation and execution of mobility scenarios to be resolved by our DRST fleet and visualise its operation.

## **Part IV**

# **Rural and Interurban Transportation Enhancement**



# A Survey on Demand-responsive Transportation for Rural and Interurban Mobility

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### Abstract

*Rural areas have been marginalised when it comes to flexible, quality transportation research. This review article brings together papers that discuss, analyse, model, or experiment with demand-responsive transportation systems applied to rural settlements and interurban transportation, discussing their general feasibility as well as the most successful configurations. For that, demand-responsive transportation is characterised and the techniques used for modelling and optimisation are described. Then, a classification of the relevant publications is presented, splitting the contributions into analytical and experimental works. The results of the classification lead to a discussion that states open issues within the topic: replacement of public transportation with demand-responsive solutions, disconnection between theoretical and experimental works, user-centred design and its impact on adoption rate, and a lack of innovation regarding artificial intelligence implementation on the proposed systems.*

## 6.1 Introduction

Access to public transportation (PT) should be generalised, as its name implies. Rural communities are often marginalised, with citizens only accessing low-quality PT. Some of the characteristics associated with rural PT are old vehicles, long and infrequent routes, and inconvenient stops. Therefore, it is common to observe higher ownership of personal motor vehicles in rural settlements (2 per household versus 1 in cities) [27].

The demand for transportation in rural areas differs from that in urban areas. It is characterised by more scattered transport requests, both in time and space, which makes the economic viability of higher-quality services more difficult. Consequently, with this shape of demand, it seems difficult to justify deploying a transport that continuously offers service, with or without passengers. Because of that, the on-demand transportation paradigm shows potential for reducing costs while increasing service quality in rural areas.

Demand-responsive transportation (DRT) systems offer displacement services adapted to the needs of their users. Initially conceived as a mobility option for impaired people and inhabitants of isolated areas [130], this mode of transport is again attracting PT providers' interest thanks to technological advances that allow users to be connected most of the time. DRT systems count on two main characteristics: on-demand mobility and adaptable flexibility. According to the specific configuration, DRT can resemble transportation ranging from high-capacity interurban buses to dial-a-ride urban taxis [57]. Thus, given a use case, it is necessary to analyse which implementation best fits the needs of the potential customers. In practice, however, implemented DRT services have a relatively high failure rate, caused by high economic costs [30, 42] and low customer acceptance, among others. In addition, the success of a concrete DRT deployment depends on the characteristics of the area it services, its population density, demand, and current transportation trends. The implementation of demand-responsive mobility has been highly studied in recent years, although mostly applied to urban contexts [21].

In this review article, we bring together papers that discuss, analyse, model, or experiment with DRT systems applied to rural areas and interurban transportation, with the intention of discussing their general feasibility as well as the most successful configurations. Political authorities from different parts of the world

have shown their interest in the improvement of rural transport with a sustainable perspective. The Spanish government, for example, has presented within its “mobility strategy” the Rural Mobility Roundtable<sup>1</sup> where it highlights, among others, the importance of demand-driven transport and the creation of dynamic routes to work towards the goal of generalised access to PT in rural areas.

The rest of the paper is structured as follows. Section 6.2 describes DRT systems and their components, introducing the challenges its implementation involves. Section 6.3 classifies the state-of-the-art work dividing it into analyses and proposals and summarising each of the cited works. Section 6.4 discusses the results and insights of the reviewed publications, with a particular fixation on the observed open issues. Finally, Section 6.5 concludes the review article by summarising the state of DRT research and stating the main takeaway points of the present work.

## 6.2 Definitions and Problem Description

This section describes DRT and provides the necessary definitions for the posterior classification of rural-DRT publications. First, we characterise demand-responsive systems according to their configuration. Then, the modelling and optimisation techniques that are classically applied to works in the area are commented. Finally, some insight is given regarding the optimisation perspective that different DRT researchers follow.

### 6.2.1 Demand-Responsive Transportation Characteristics

DRT systems have a series of standard elements present in all of them. Different authors apply different labels to those elements. For the current work, we have followed the terminology described in this survey [152].

In a DRT system, a *service* is the departure of a vehicle to serve the transportation requests it has assigned. One service is generally tied to a concrete area or line assigned to the transport. In contrast, a *route* is the specific path the vehicle

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<sup>1</sup><https://esmovilidad.mitma.es/mesa-de-movilidad-rural> (Accessed on 01/12/2022)

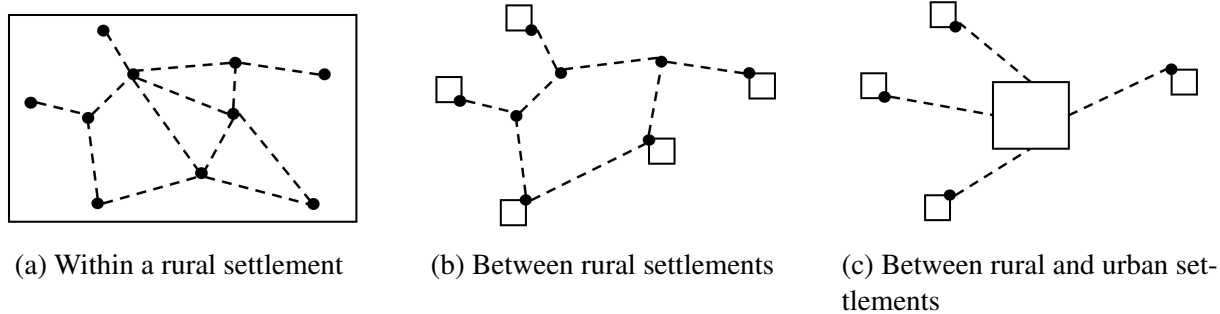


Figure 6.1: Observed operational patterns for rural demand-responsive transportation systems. Boxes indicate rural/urban settlements. Black dots represent stops. Dashed lines represent demand-responsive lines. Pictures (a) and (b) are cases of many-to-many transportation, while (c) represents a many-to-one model.

follows connecting all the pickups and drop-offs. A route does not necessarily include all existing stops in a line or area. Customers are picked up and dropped off in a predefined set of *stops* within the serviced area or line. Alternatively, a *door-to-door* service can be offered, in which any user-specified location within a particular area may act as a stop. This type of mobility is thought to be *shared*; i.e.: multiple customers are served by the same vehicle. Typical vehicle choices for demand-responsive services include a taxi-like car with a capacity of 4 passengers, mini-vans with 9 to 12 seats, and mini-buses or buses with 20 to 30 seats, respectively.

Many operational patterns exist for DRT. Specifically, for rural-DRT, we find the following: transportation within rural settlements, transportation between rural settlements, and transportation between rural and urban settlements. In practice, these cases can be reduced to two systems: *many-to-many*, with a set of multiple origins and destination locations, and *many-to-one*, where origin and destination locations share a unique pick-up or drop-off point. The last type is usually the so-called feeder line, where a flexible transportation service is used to move passengers to a different, less accessible service (for instance, communications from rural settlements to an airport). Fig. 6.1 shows a schematic representation of the commented used cases.

If the customer is required to send a *request* to access transport the service is

provided *on-demand*. The time between sending a request and the customer's pick up is the *lead time*, and it is used to adapt the fleet operation or *planning* to include such a request. In a stop-based operation, the customer will be assigned a stop from which it will be picked up. On-demand systems can operate in real-time, accepting last-minute bookings, or with a hybrid approach, accepting bookings in advance too. DRT systems which are not on-demand are also possible. These systems consider current demand or demand predictions for service planning but do not require requests to run.

The period of time for which the DRT service is planned and optimised is referred to as *planning horizon*. The duration of planning horizons is usually a whole day. In addition, the operator may plan for a few hours to adapt to high/low demand periods. According to the influence of the demand data on the service planning, the system will be *fully-flexible* if routes are planned from scratch according to current demand or *semi-flexible* if a predetermined plan exists but vehicles are allowed to modify it influenced by demand.

## 6.2.2 Modelling and Optimisation Techniques

Once the specific type of DRT system has been chosen, it must be modelled and tested to check its performance and adjust its attributes. We discuss below the different steps this involves, citing relevant research and the methods their authors employ. Please be aware that not every paper cited in this section explores rural-DRT.

Most DRT works are set in a specific settlement or area. In general, the main transportation network (roads, highways) of the area is mirrored thanks to services like Open Street Map ([openstreetmap.org](http://openstreetmap.org)) or Open Sourcing Routing Machine (OSRM, [project-osrm.org](http://project-osrm.org)) [41]. Ideally, the actual organisation of the area, its types of districts, population, or socio-economic reality, among others, should also be considered. Authors in [80] describe a seven-step analysis method for the optimisation of any transportation system, based on reproducing the features of the currently implemented transport service (that would potentially be replaced). Alternatively, some works employ grid-like modellings of the area where the system will run [23]. The actual routing of each fleet vehicle represents one of the



main challenges of DRT services, as it must be performed in real time. Innovative heuristic algorithms [34, 114] aid in this respect.

Demand modelling is also crucial. Passenger demand has two main aspects: (1) frequency and intensity and (2) shape (location of origin-destination pairs). Demand attributes can be extracted from datasets of different transportation modes and extrapolated, as in [60], where taxi data is used. Moreover, real data of pilot DRT services [150, 29] can be reproduced when available. However, the most observed technique is the use of synthetic demand data that can be generated statistically [23], based on socio-demographic information [153], via surveys [29, 136, 41] or generated in a (semi-)random [151] way according to the properties of the reproduced area (population, age, occupation, vehicle ownership). Finally, if traffic intensity data is available, it is useful to include it in the model, although not as relevant for rural areas with respect to city-centred studies, since the former tend to have lower intensity.

The operation of the DRT system requires automated planning and scheduling of vehicle services. At the same time, these tasks need information on the time and travelled kilometres that any detour would imply, which makes routing algorithms also necessary. In addition, since it is common to find online systems that accept real-time requests, the computation time for detours and new request insertions must be kept low. The use of multimodal planning [41] is common to solve the scheduling of vehicle services. Moreover, some simulation platforms, such as MATSim [9] include their own implementations of the algorithms mentioned above. These implementations usually employ (meta)heuristic techniques [153] that optimise vehicle-passenger assignments (insertion heuristics [18], for instance) or vehicle routing in a short computational time. Besides that, other less exploited techniques such as automated negotiation could be used to decide assignments from a decentralised perspective [14].

Finally, to observe the system's dynamics and its operation and adjust its attributes, it is necessary to simulate it. This can be performed through mathematical modelling [80] provided detailed data is available. However, a more popular way of achieving this is through multi-agent simulation (MAS). Among the observed choices we find NetLogo [144], used in [62], the already mentioned MATSim, and even custom simulators [117, 41].

### **6.2.3 Optimisation Goals**

The main goal of people transportation services is to supply the displacement needs of its users. Ideally, the operation of the service shall be performed by optimising three factors: (1) the economic viability of the service; (2) the customer's experience (or quality of service); and (3) the environmental impact of the service. These three factors are translated into scopes when it comes to transportation research, and thus we can find works that assess one (only operator perspective [93]), or many of them from a multi-objective perspective (passenger and operator perspectives [85]). Optimising customer experience implies reducing passenger travel times, whereas economic viability is ensured by reducing operational costs. Finally, optimising sustainability requires reducing vehicle travelled kilometres (VTK).

The greatest challenge of demand-responsive transportation systems is finding the equilibrium among the above factors to offer a competitively-priced, economically viable, and flexible mobility alternative to private cars and traditional public transportation. For the case of rural-DRT, economic viability is especially difficult, taking into account the relatively low demand.

## **6.3 State of the Art Classification**

This section presents a classification of the relevant literature found while researching the topic. Given the heterogeneity observed among the articles, they have been grouped by two criteria. On the one hand, the first group encapsulates studies, surveys, and analyses on the implantation of DRT solutions for rural areas. On the other hand, the second group presents papers that include at least an explicit DRT system proposal and experimentation to evaluate it. Both types of work offer reflections and insights into the viable application of on-demand mobility to areas with scattered populations and low demand.

### **6.3.1 Literature Retrieval and Overview**

The Google Scholar and Scopus search engine were used to retrieve articles and book chapters relevant to the topic. The results were filtered applying the following rules: 1) the term "demand-responsive" had to be present in the title, abstract, or

keywords of the publication, and 2) at least one of the terms “rural”, “rural area” or “interurban” had to be present in the title, abstract, or keywords of the publication. Using the above criteria, the first search yielded 34 articles. Of these, 9 were discarded because the algorithms or systems they described did not fit the rural perspective of our review paper. The keywords “rural” and “interurban” could be present in the abstracts, but that did not guarantee that the characteristics of the systems researched by the authors matched those of rural or interurban mobility. Therefore, only papers that explicitly modelled low demand with scattered residents or assessed a rural interurban scenario were retained. Once filtered, the batch of relevant publications had a relatively small size of 25 publications. The fact is that rural-DRT solutions are less explored than their urban counterparts, probably because of factors such as scarce data availability and a lack of general interest until recent times.

In addition to the few publications, the degree of detail regarding the DRT systems described in them varied considerably. In general, all authors describe at least the operation of the basic components of any transportation system. However, just a minority explicitly state their system’s constraints, the objective function(s), or the technology employed to build their proposals. Finally, it is worth mentioning that each proposal is tailored to the rural area it serves, which also differs for each work.

Given the described situation, we have chosen to summarise the publications on this topic one by one, giving as much relevant detail for each of them as possible. Nevertheless, two main classification criteria have been applied to divide the publications: analytical works, discussing challenges and studying the implementation of DRT in a specific context (Section 6.3.2); and experimental works that explicitly model, implement and simulate a DRT system (Section 6.3.3).

### **6.3.2 Analyses and Surveys**

This subsection groups the state-of-the-art literature which assesses the challenges, potential benefits and contributions of implementing DRT for rural mobility. Most of the cited works develop their analyses around a main topic, which is shared among some, but present their own methods and conclusions. Following, we present the contributions grouped by the main topic they discuss.

### **6.3.2.1 Success and Failure of DRT Systems**

One of the most historically studied topics in DRT history is the success and failure of deployed systems. Works in this line give important insight that PT providers must consider when designing a system. Enoch et al. assess the failure of DRT systems in [42]. The authors concluded that DRT projects are often not realistically costed or designed with a full understanding of the market they are to serve. A pattern was observed in which providers offered too flexible a service, including costly technological systems, when they may not be needed. In contrast, the authors recommend an incremental approach as a more sensible option. Compared to conventional PT operations, DRT requires more marketing effort and skills, but above all, it requires new skills in working in partnership. The failure in partnerships is where the root of DRT failure is often found.

G. Curry and N. Fournier [30] review DRT and Micro-Transit implementations to assess their performance. High failure rates stand out in their findings. 50% of the systems last less than 7 years, 40% last less than 3 years, and about a quarter fail within 2 years. In the UK, 67% of DRT services have failed, and in Australasia, 54%. The results indicate that simpler operations (e.g., many-to-few or route deviation) had lower failure rates compared to more complex many-to-many services. The authors develop a cost analysis that shows a strong and definitive link between DRT failure and higher service costs.

### **6.3.2.2 Replacing Classic PT With DRT**

Many analyses focus on a particular rural settlement and aim to replace or optimise the currently implemented means of PT. Ryley et al. [130] investigate the contributions of DRT to sustainable PT. Their study surveys the public of both urban (Rochdale, Manchester) and rural (Melton Mowbray, Leicester) areas of the UK. Six DRT service variants are explored using mixed logit models; from those, a rural hopper service linking a number of rural settlements to a market town fits our research. Regarding that system, authors find the in-vehicle time of passengers is longer than normal, as the alternative to the DRT service is private motorised vehicles. Longer times are mainly caused by the dispersion of the served population, and the need for door-to-door as opposed to stop-based services, necessary due to the predominantly elderly and/or mobility-impaired users.

Coutinho et al. [29] assess replacing a fixed public bus line with a DRT system to service the rural surroundings of Amsterdam, the Netherlands. Their analysis focused on indicators such as distances, ridership, costs, greenhouse gas (GHG) emissions and the population's perception of DRT. Their results expect a drop in ridership which is compensated by mileage and operating time-frame reductions. There is better overall efficiency with DRT compared to the fixed service. The number of travelled kilometres, operational costs and GHG emissions per passenger were smaller.

C.-G. Roh and J. Kim [127] analyse and propose an optimisation for six small bus routes in the rural city of Yangsan-si, South Korea. Geographic Information Systems (GIS) were used to compare and review the planned routes and operation status of each route, while improved DRT operation methods were studied based on these operations patterns. A more suitable DRT small bus operation model for each route was proposed as a conclusion.

### 6.3.2.3 DRT Systems' Adoption Rate

The adoption rate of newly deployed DRT systems is tightly related to their success. Some authors centre their assessments on this topic. Wang et al. [156] discuss the DRT adoption rate in the rural area of Lincolnshire, England. The authors argue that car ownership, the aging population, and cuts in public spending threaten the traditional public bus services that operate in rural settlements. DRT, however, faces a series of challenges for its successful implementation. Through the analysis of various factors, it is determined that people with disabilities, those travelling for work, and those who live in less densely populated areas are more likely to travel by DRT. In addition, a gender-based analysis reveals females have a higher propensity to use DR services compared to males below retirement age. However, the trend vanishes upon reaching retirement age. This, for the authors, indicates an emerging market potential from the retired male market segment, and thus service providers should design their systems considering it.

Anburuvel et al. [8] run a survey to explore the willingness to accept a DRT service for the spatially scattered population of a rural region of Sri Lanka. The survey pointed towards economic attributes (income and vehicle ownership), sociocultural attributes (age, gender, and education), and mobility needs (travel fre-

quency and access distance/cost) as the primary factors which decided the choice of a transport mode, thus begin more relevant in the decision of the deployment of a new service.

Schasché et al. [134] elaborate a review on the conflicting expectations and weak user acceptance of rural-DRT systems. Their paper creates an overview of the development in the research field, focusing particularly on user-oriented research, detects conflicting performance expectations towards DRT services that complicate their success, and identifies discrepancies between perception and empirical design studies. The findings suggest a need for more focus on rural areas when attempting to reduce the use of private combustion engine vehicles in favour of public transport and successfully establish DRT services as well as further research into specific user groups. The main take-away points are the following: In rural areas, personal factors such as age, gender, and private car access are found to be of stronger influence on user acceptance than in urban areas. Service-related factors like time reliability and booking methods have a higher impact on rural transport mode decisions than in urban settings. Finally, knowledge of DRT service and information provision also appears more influential for users in sparsely populated regions.

#### **6.3.2.4 Reviews on Smart and Sustainable Mobility for Rural Areas**

Some of the most useful theoretical contributions come from those works that group relevant publications, much like the present paper. The perspectives and criteria for the grouping are what differentiated one review on a concrete topic from another. Agriesti et al. [6] aim to build the case for a renewed research effort about smart mobility in low-density areas. The authors perform a wide surveying effort across Estonian municipalities, focusing on the outputs from rural and small suburban centres. The results report the main mobility challenges across the region and what hindering factors are preventing envisioned solutions. Tracking social behaviour, changing travel patterns, and social inclusion stand out among these challenges. Technology implementation is also identified as a key priority, particularly regarding traffic management and planning practices.

Poltimäe et al. [120] present a review of papers dealing with inclusive and sustainable mobility systems for rural areas. After analysing many proposals, the

authors group them into four categories: semi-flexible DRT, flexible door-to-door DRT, car-sharing, and ride-sharing. The main conclusion of their study is that single mobility solutions are rarely applicable to all rural travellers. Therefore, the future lies in multimodal mobility, considering that strong spatial and temporal synergies exist when combining different solutions. Success factors for sustainable rural transportation are identified, among which accessible and easily understandable information on routing, booking, and ticketing systems, as well as cooperation, shared values and trust between various parties, stand out. Finally, the importance of integrating the needs of various user groups for implementing environmentally, socially, and economically sustainable mobility solutions in rural areas is emphasised.

#### 6.3.2.5 Other Analytical Contributions

Given the strong relationship between transportation systems and the area they service, some authors focus their surveys and proposals on specific topics which are relevant in their case. Abdullah et al. [3] assess the service quality of two DRT bus services operating in Lahore, Pakistan, through a questionnaire. The surveyed data reflected service attributes and bus ambience as significant predictors of overall customer satisfaction.

F. Heinitz [55] approaches the improvement of rural mobility through incentives for private vehicle drivers to share their vehicle with other passengers for a concrete journey. The author builds a framework that defines steps to take when considering the introduction of DRT elements to a rural mobility scenario. His case study, set in the Schmalkalden-Meiningen area, Germany, takes into account German legislation. The author's conclusions show he understands as a mistake the proposal of a whole DRT solution from scratch for a certain rural area. Instead, he bets on modal integration and the development of high-adoption ridesharing among citizens, as private vehicles are the best approach to the mobility patterns of rural inhabitants.

F. Cavallaro and S. Nocera [24] study the novel concept of integrating passenger and freight transportation in flexible-route vehicles for rural areas. The developed case study is centred in the municipality of Misano Adriatico, Italy. The performance of the service is evaluated through a selection of financial, operational,

environmental, and social key performance indicators. The results of the analysis revealed a reduction in kilometres travelled, fuel consumption, and air pollutants, together with an increase in the area covered by the service, an increase in potential daily deliveries (for freight transport), and an increase in the occupancy rates of vehicles (for passengers).

### **6.3.3 Proposals and Experimental Work**

This subsection groups the state-of-the-art literature which explicitly describes either a complete DRT system or some crucial part of it, including proposals that seek to optimise the system's operation or that simply test a particular approach for modelling, scheduling, or simulation.

Two main criteria have been used to divide the publications according to the system's proposed features. On the one hand, systems following many-to-many locations' operational patterns are separated from those using a many-to-one scheme. On the other hand, within each operational pattern, systems are split into those with fully-flexible routing and scheduling and those with semi-flexible ones.

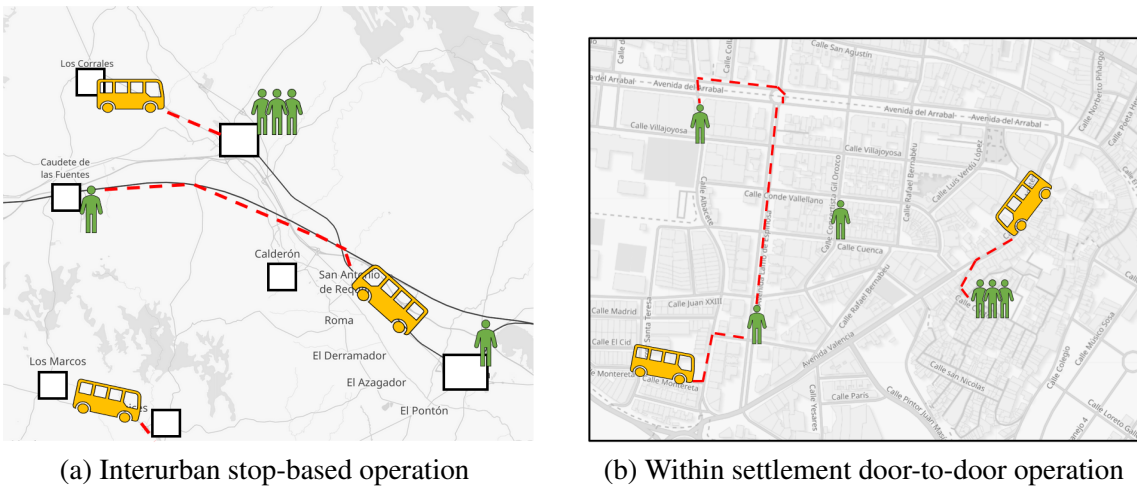
Fig. 6.2 illustrates different DRT configurations that were found among the proposals analysed in this section.

#### **6.3.3.1 Many-To-Many Operational Pattern**

##### **Fully-flexible Scheduling**

Among the analysed works that implement and validate concrete proposals, a few aim to enhance a commonly used technique or define approaches that deviate from the norm. Van Engelen et al. [151] propose an enhancement to insertion heuristics by including demand anticipation. Their algorithm is tested over the Tata Steel IJmuiden area in the Netherlands. The demand forecast is considered when a new request arrives in the system and is used to filter the number of fleet vehicles that can serve it. Generally, a vehicle will have enough free seats to serve passengers (demand) at the next stop on its route. Demand forecasting is applied to decide the probability that the next stop will have more demand than what the system currently considers. A vehicle may be rerouted to a stop with an expected demand greater than its current seat availability if the operator has "low confidence" in





(a) Interurban stop-based operation

(b) Within settlement door-to-door operation

Figure 6.2: Graphic representations of demand-responsive transportation systems operating with different configurations. Passenger demand is depicted by green human icons, whereas vehicles are portrayed by yellow buses. Vehicle routes are indicated with red dashed lines. Picture (a) reproduces an interurban operation, where settlements, indicated with white boxes, act as stops to travel from/to. Picture (b) depicts a door-to-door operation within a rural settlements, in which passengers can ask for a ride from any location within the town.

the demand forecast; this implies taking a risk. Conversely, when there is high confidence in the prediction, vehicles with a higher number of available seats than the current demand are rerouted, thus making room for the estimated demand as well. The authors compare their method to traditional insertion heuristics. The results show that by combining their proposal with empty vehicle rerouting 98% of the baseline rejected requests are eliminated, and travel and waiting times are reduced by up to 10 and 46%, respectively.

K. Viergutz and C. Schmidt [153] propose a case study on the rural town of Colditz, Germany, comparing conventional public transportation against DR services. The conventional transportation consisted of a bus line, whereas for the DRT two proposals were tested. Both DR proposals were on-demand, many-to-many, and fully-flexible. However, one of them operated stop-based with 5 automobiles and the other door-to-door with 10 vans. Their system declared constraints on the number of fleet vehicles, vehicle capacity, the maximum waiting and passenger travel time, and walking distance to the nearest stop. The scheduling of services

was performed by a heuristic algorithm that allocates the nearest idle vehicle to each new request. The authors used surveyed and statistical data to reproduce realistic demand for the experimentation. Then, multi-agent simulations were run for each fleet configuration. Their findings revealed that, for the stop-based scenario, the number of passengers increases compared to conventional PT, but also does the fleet necessary to keep a good level of service (four vehicles vs one). Moreover, dynamic, real-time vehicle assignment requires hard-and software, which involves additional expenses to already financially limited rural PT providers. An excess of dynamism in PT (absence of lines and timetables), according to the authors, may be a strain on customers, leaving them at the mercy of their technical capabilities for managing booking applications. The work concludes that ultra-flexible DRT services are not the panacea for the rural PT sector, especially not in the case of a free-floating, DR, door-to-door service. Economically speaking, the authors remark on the importance of autonomous vehicles for a more efficient DRT.

Dytckov et al. [41] explore by means of simulation the benefits of replacing existing bus lines in the rural area of Lolland, Denmark, with a DRT system that better fits the low mobility demand. Authors build their own microsimulator joining together many open-source tools: a multimodal travel planner for scheduling (OpenTripPlanner), a library for solving vehicle routing problems (jsprit), OSRM to prepare data for the routing solver, and finally a custom event-driven simulator. Their proposal consists of an on-demand, fully-flexible, many-to-many, stop-based DRT system served by eight-seat minibusses. During the experimentation, constraints on request lead time, time window, trip time, driving time, and vehicle capacity are defined and modified. In addition, authors consider penalties for rejected requests and for the dispatching of new vehicles. The main assumption of their study is that transportation demand does not change when changing from buses to a DRT system. The simulation results show the potential to reduce costs and  $CO_2$  emissions.

R. Morrison and T. Hanson [106] explore the concept of volunteer driver programs (VDPs) to replicate a door-to-door DRT service in rural areas. A rule-based system was developed to describe the operation of a VDP. The system was calibrated and validated with one year of New Brunswick (Canada) Volunteer Driving database data. Then, the multi-agent simulator Netlogo was used to implement and study a simple agent-based VDP. The system operation was simulated and stressed

through many scenarios that posed challenges. Finally, VDPs were understood as a viable solution, although the authors remark on the need for additional research regarding actor (users, drivers, dispatchers) interactions.

Matsuhita et al. [103] propose two methods for promoting tourism use of a demand transportation system operated in the rural town of Aizumisato, Fukushima Prefecture, Japan. These proposed methods are a hybrid operation of both conventional on-demand transportation and scheduled transportation which is compatible with Google Map route search and the posting of times and routes using virtual stops. The effect of the proposals is studied utilising the SUMO microscopic traffic simulator. The results show that the proposed system can operate on time without any problems, although the waiting time for passengers increases compared to the current method. The average maximum number of passengers that can be picked up and dropped off within 30 minutes is 12.3, which means that the system can operate with an increase of about four passengers compared to its current maximum capacity during peak hours.

### **Semi-flexible Scheduling**

Bruzzone et al. [20] explore the implementation of a DRT solution for the rural town of Velenje, Slovenia, given the poor performance of its current transit system. The researchers surveyed a focus group to establish the faults of the current transportation and the citizen's attitude towards on-demand mobility and cycling. The authors had the parallel objective of moving demand away from private motorised transports. Their final proposal combines two new DR bus lines and an electric bike-sharing system (e-BBS). The main DR line offers a semi-flexible, many-to-many service with a scheduled route and several on-demand stops; meanwhile, the secondary line operates in a fully-flexible manner, feeding the main line with a many-to-one<sup>2</sup> service. The e-BBS has two roles; feeding both DRT bus lines and offering accessible transportation for short displacements within the town's neighborhoods. Cost analysis reveals the proposal would achieve better service quality with the same financing the current public transportation is getting, reaching a higher percentage of the population.

Li et al. [82] propose a method for transit scheduling of DRT systems based on

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<sup>2</sup>Bruzzone et al. use the term few-to-one, which would be a variation of a many-to-one operation with a relatively small number of origin stops.

optimising urban and rural transportation stops. Their method clusters passenger reservation demand through a DK-means clustering algorithm, identifying later fixed and alternative stops for the transportation system. Then, a genetic simulated annealing algorithm is proposed to build the bus schedule, obtaining a flexible-route DRT service that promotes urban-rural connections. Their proposal is validated in the northern area of Yongcheng City, Henan Province, China. Comparing their final model against the existing regional flexible buses, results show the optimised bus scheduling reduced the operating cost by 9.5% compared with that of regional flexible buses while reducing the running time by 9%. In addition, the authors compare their final proposal to that obtained merely after the DK-means clustering of stops and observed a 4.5% reduction in operational costs and 5% reduction in run times, thus proving the genetic simulated annealing step crucial to improve the service further.

### **6.3.3.2 Many-To-One Operational Pattern**

#### **Fully-flexible Scheduling**

Vehicle dispatching (from the current stop to the following one) in DR services is generally computed as a function of time, ensuring early service to boarded customers and waiting at stops only when there is enough slack time. Marković et al. [93] propose a threshold policy to dispatch vehicles according to the number of onboard passengers. For the experimentation, a flexible, one-to-many, door-based DR service is implemented, transporting the customers from a terminal to their homes. The authors adjust their proposal through numerical simulations set in a rural context, with demands ranging from 21 to 30 passengers per hour. They aim to find the threshold that reduces hourly costs as well as the adequate fleet size. The results indicate that the optimal threshold is a function of time-varying demand and thus must be adjusted for different times of the day. In contrast, the fleet size must be adjusted accordingly.

J. Bischoff and M. Maciejewski [18] propose an optimisation for the operation of a DR fleet based on balancing vehicles according to the expected trip demand. Their method ensures that the spatial availability of vehicles follows the spatial distribution of demand in the (near) future. To test their proposal, the authors implement a feeder service that connects inhabitants of rural areas to other high-capacity

means of transportation. The system operation is simulated with MATSim. The passenger-vehicle allocation is done through insertion heuristics where, given a request, each feasible insertion point is assessed and the best one is chosen. The balancing of the fleet is done as follows: First, rebalanceable (with enough slack time) and soon-to-be-idle vehicles are grouped. Then, the amount of demand per zone is estimated according to historical data. With that, the surplus (extra) vehicles in each zone are computed, and vehicles are dispatched from routes with a positive surplus to those with a negative one. Such dispatching aims to incur the shortest possible movement of the empty dispatched vehicle. The results show that customer waiting times can be cut up to 30% with no increase in VTK, meaning the rebalancing improves service quality at barely any monetary cost.

Schlüter et al. [136] assess the impact an autonomous DRT system would have in the specific case of linking an urban and a rural area. Specifically, their work is centred in the city of Bremerhaven, Germany, and its surrounding rural settlements of Lengen, Schiffdorf and Loxstedt. This constitutes a fairly wide area, leading the authors to two different assessments, centring one of them in the rural area. For that, an on-demand, door-to-door, many-to-one, fully-flexible service is established. As for the implementation, authors use the multi-agent simulator MATSim [59] with DRT modules. The road network is created with Open Source Routing Machine (OSRM), reproducing the real one. The system optimises the operation through insertion heuristics, and the demand is generated following population statistics and surveys. The experimentation studies the replacement of the MIT (motorised individual transport). Results show that at least 1800 vehicles with a capacity of 6 passengers are necessary to provide a service rate of above 95%. Passenger waiting time values are below 13 minutes in this manner and decrease with an increasing number of DRT vehicles. The average travel time of the agents increases by around 66% when switching from a car-based scenario to pure DRT. Their results distil the following assessments: the number of vehicles can be reduced by more than 90%. By that, several negative side effects such as congestion, noise, fragmentation, or land sealing can be mitigated, allowing new perspectives for urban planning and regional management. The replacement of human drivers with an autonomous driving system leads to a significant reduction in operational costs. However, the authors state that without the use of fully automated driving systems, DRT cannot compete economically. Finally, the limitations of this

work come from the available data, which does not provide sufficient depth, the exclusion of public transportation from the simulated baseline framework, and the replacement of the entire MIT of a region, which is a radical theoretical approach. Authors remark that the adoption rate of new mobility, such as DRT systems, and the acceptance of fully automated vehicles determine the realistic percentage of MIT that can be replaced.

Calabrò et al. [23] explore the benefits of DRT feeder services with respect to a fixed-route (FR) service. Even though their experimentation takes place in a virtual road network, feeder services are one of the go-to DR modes in rural settlements, and thus we consider them relevant for the present review. The authors model a stop-based, many-to-one, fully-flexible, on-demand service. Their implementation employs basic insertion heuristics and a demand generation based on Poisson distributions. The system operated on a node-joint network. The simulations reveal that DRT is preferred in peripheral areas where the space between stops is high and during off-peak demand periods. In contrast, FR service performs better during peak demands. The recommendation for a transport operator is, therefore, to switch services according to the demand.

### **Semi-flexible Scheduling**

Lakatos et al. [80] explore the substitution of a regular bus line operating between 11 “dead-end” villages in rural Hungary. They describe a seven-step analysis method for the optimisation of any transportation system. Such a method attaches particular importance to the characteristics of the current transport service (the one that would potentially be replaced). Their study is conducted through mathematical modelling fed by surveyed data. The study proposes three different DRT solutions. All proposals are on-demand and stop-based but vary in operational pattern and flexibility. Their first system (1) completely replaces all bus connections with a DRT service, modelling a many-to-many, semi-flexible operation. The second one (2) aims to replace only the detours that the bus has to do from the main line with a DRT service, keeping the regularly scheduled bus service just along the main line, describing a many-to-one, semi-flexible operation. Finally, the last proposal (3) introduces DRT just as an extra service connecting settlements with the present main route, therefore establishing a feeder for the main bus service. In this case, the operation would be many-to-one and fully-flexible. After analysing all three

proposals, the main bus line is kept for four of the settlements and the connection among all of them, whereas the other seven villages implement a DRT service, with one minibus each, connecting the stops within them to the main line. This configuration feeds the main line and avoids bus detours. The new configuration's cost does not exceed that of the traditional transportation system but increases the level of service with better frequencies and more connections. The authors emphasise the importance of developing policies with the public services for the viability of the rural-DRT system as well as the limitations of their method, which mainly considers ridership as an influencing factor.

## 6.4 Discussion

The cited works have been summarised in a series of tables. Table 6.1 gathers the works from Section 6.3.2 whereas Table 6.2 collects those described in Section 6.3.3.

### 6.4.1 Summary of Results

Observing Table 6.1, certain topics stand out as the most investigated. DRT systems' failure as a general public transportation service has been widely studied. Such a topic is closely related to the adoption rate these systems have once deployed; the number of users that switch from their current transportation alternatives to the new DRT system. In addition, many authors aim to replace or improve the current PT of a rural area with a DRT solution. This is also the case for most of the assessed system proposals. Regarding the observed challenges for a viable and successful DRT system deployment, these can be grouped into economic challenges: unrealistic or excessively flexible operation, lack of partnerships, and poor adoption rate; and social challenges: scattered population, disparity among technological skills, low income, different social behaviours and travel patterns, and high ownership of MIT. Both analytical (Table 6.1) and experimental works (Table 6.2) acknowledge the potential of DRT to improve service quality and thus passenger satisfaction, and reduce vehicle mileage and operating hours, thus reducing the system's environmental impact too. Besides that, a series of factors increment the

Table 6.1: Cited survey and analysis works classified by main topic, data-gathering method, and identified challenges and potentials. Acronyms: DRT (demand-responsive transportation), MIT (motorised individual transport), PT (public transportation), VTK (vehicle travelled kilometres).

	Topic	Method	Challenges	Potentials
[42]	Success and failure of DRT systems	Analysis of failure factors	Unrealistic design, excessive flexibility, lack of partnership, high service costs	Simpler operations (in pattern and flexibility)
[30]		Review of DRT database		
[130]	Replacement/optimisation of public transportation with DRT	Citizen survey	Financial viability, institutional barriers	Mileage reduction, operating time-frame reduction, improved passenger load
[29]		Historical overview of DRT systems	Population's perspective, drop in ridership	
[127]		Modelling	Populations' aging and decline	
[156]	Adoption rate	Factor analysis	Ageing population, cuts in public expense	Market for commuters and retired population
[8]		Citizen survey	Scattered population, low income, high vehicle ownership	User-focused deployment of services
[134]		Literature review	Disparity among perception and empirical design	Specific user group research
[6]	Smart, sustainable mobility for rural areas	Citizen survey	Social behav. tracking, changing travel patterns, technology implementation	Multimodal mobility Cooperation among parties User group integration
[120]		Literature review	Mobility solutions tied to specific travellers	
[3]	Service quality	Questionnaire	High costs, institutional barriers	Customer satisfaction given by vehicle ambiance
[55]	Incentivised shared mobility	Modelling	Excess of MIT in rural areas, uneven travel patterns	Modal integration, citizen cooperation
[24]	Passenger-freight transportation	Modelling	Limited resources to guarantee access to main territorial hubs, underutilised PT	Higher area of service, higher occupancy, reduction in VTK



Table 6.2: Cited experimental works classified by operational (Op.) pattern, route flexibility, stop configuration, booking necessity, fleet size and capacity, and optimisation (Opt.) perspective (persp.). Acronyms: e-BBS (electric bike-sharing system).

	Op. pattern	Flexibility	Stops	Booking	<# vehicles>x<# seats>s	Opt. persp.
[151]	many-to-many	fully-flexible	stop-based	on-demand	100x5s	passenger
[153] (1)			stop-based	on-demand	5vx4s	operator
[153] (2)			door-to-door	on-demand	10x6-14s	passenger
[41]			stop-based	on-demand	29x8s, 19x8s	operator passenger environment
[106]			door-to-door	on-demand	4s (private cars)	passenger
[103]			door-to-door	on-demand	1x9s + 2x4s	passenger
[20] (1)		semi-flexible	stop-based	not needed	1 bus + e-BBS	passenger
[82]			stop-based	not needed	1x20s	operator passenger
[80] (1)			stop-based	on-demand	11x8s	operator passenger
[20] (2)			stop-based	on-demand	1 bus + e-BBS	passenger
[93]	many-to-one	fully-flexible	door-to-door	not needed	6x10s	operator
[18]			door-to-door	on-demand	100x4s	operator passenger
[136]			door-to-door	on-demand	1800x6s	operator passenger
[23]			stop-based	on-demand	3x20s, 5x8s, 10x4s, 20x2s	passenger
[80] (3)			stop-based	on-demand	1x50s + 11x8s	operator passenger
[80] (2)			semi-flexible	stop-based	on-demand	1x50s + 7x8s

chances of a successful deployment of DRT: semi-flexible operations, user-focused design, user-group research, partnerships with public and private institutions, and the integration of different modes of transportation.

Regarding experimental works, Table 6.2 shows the most popular trend in terms of DRT systems' configuration: a many-to-many operational pattern with a fully-flexible routing, servicing a series of stops with an on-demand shared mid-capacity vehicle. The proposals mainly aim to replace or improve the operation of the current means of PT in a concrete rural area. In some cases, a new system is proposed from scratch to serve a specific unfulfilled displacement need. Among the observed used cases, most of them serve a series of locations freely, whereas a

minority propose feeder systems that bring passengers to a higher-capacity, less flexible transportation network. Finally, it is usual that authors aim to optimize, at least, the passenger's perspective. Most of them also include an operator perspective, which is closely related to the economic viability of the service. Finally, a minority explicitly comments on the environmental improvements their system brings.

## **6.4.2 Open Issues**

Following, the open issues and key insights distilled from our classification are discussed, providing a basis for reflection on the challenges and indicating possible solutions and recommendation.

### **6.4.2.1 Replacement and Optimisation of Existing PT With DRT**

The reviewed literature shows the difference among authors' insights regarding the performance of their proposed systems. For a fair assessment of a DRT proposal's performance, we must consider the context in which the system is proposed and thus its intended goals. The metrics that the authors will give importance to in their research depend on those goals. For instance, when it comes to public transportation optimisation, usual metrics are passenger waiting and travelling time, vehicle travelled kilometres (VTK), and greenhouse gas (GHG) emissions. If a DRT system is proposed to replace or complement the current public transportation system, the research will focus on reducing passenger waiting and travelling time, VTK and GHG emissions. In contrast, a DRT service may be planned to introduce public transportation in an area where there are no mobility alternatives besides motorised individual transports (MIT). In such a case, the research will focus on the level of adoption rate of the new service and the reduction of MIT in favour of public transportation.

Most of the cited works propose a partial or a complete replacement of the traditional means of transportation already implemented in a chosen rural area in favour of a new DRT solution. Those aiming for total replacement usually keep elements of the old transportation system (such as stops) in the DRT service. This approach eases the comparison between new and previous transportation systems.

However, it also facilitates results with lower VTK and, therefore, GHG emissions, as generally with DRT some of the stops along a vehicle line are optional. If the DRT is implemented as a door-to-door service, VTK and GHG may increase with respect to the existing means of PT, and thus an improvement in service quality through time reduction and the servicing of a wider area gain more relevance.

The substitution and improvement of preserved elements of the current PT of an area should also be assessed when aiming to improve its operation. As in [82], demand distribution and stop location can be studied and modified to fit the new proposal's characteristics better.

#### 6.4.2.2 Disconnection Between Analysis and Proposals

From a general perspective, comparing the potentials that DRT offers (Table 6.1) with the most popular system configurations (Table 6.2), there appears to be a disconnection between theoretical and practical works. Even though surveys conclude on the benefits of simpler, less flexible operations and the inclusion of multimodality, the proposals present mostly fully-flexible services, and only some of them [20] consider a different transportation mode (electric bike-sharing) to complement DRT. Some authors [30, 42] agree that an excess of dynamism in demand-responsive operation can be too economically costly for the system's long-term sustainability, especially when the level of demand does not justify such a level of dynamism. The general conclusion of analytical works seems to favour semi-flexible systems, with elements from scheduled transportation (non-flexible) combined with on-demand, dynamic operation.

As a relatively new field, DRT lacks standardised systems, leading to a plethora of proposals, each with its own unique "name". Despite the abundance of ideas, a closer examination reveals that most systems are strikingly similar, varying only in minor details. Furthermore, there are few works that delve into the attributes of these models. Although it is expected to explore various algorithms and techniques in a field with many open issues like DRT, authors should focus on the specific contributions their algorithms and system models bring to passengers, operators, and drivers. It is crucial to adjust configurable components such as stops, assignments, and vehicle capacity to suit the specific real-world use case of the system.

Authors in [55, 120] comment on the importance of the integration of different

modes of transportation to truly match the rural area inhabitants' mobility requirements. In addition, partnerships between the transportation provider and other entities have been identified as a factor contributing to DRT success. One of the many ways multimodal transportation and partnerships can be promoted is through mobility hubs [128], physical locations where different modes of transportation are integrated. Mobility hubs provide travellers with options for transfers between various transport systems in order to facilitate the exchange from one mode of travel to another. Moreover, they can also include amenities like shops and restaurants, making them attractive places to visit while travelling. Given the high percentage of failed DRT systems, we consider the implementation of mobility hubs must be studied together with the topic at hand.

#### **6.4.2.3 User-Centred Design and Adoption Rate**

It seems evident that a transportation system has to adapt to the area it serves. Elements such as routes, stops and vehicles take into account the geography and spatial-temporal demand of the area. However, when it comes to classic transport systems, the way they operate remains the same regardless of where they are implemented. In the case of DRT, generalist solutions have no place, even less so in rural areas. Their necessary flexibility, combined with the low and distributed demand, forces an operation tailored to the reality of the system's potential users.

How well a system is adapted to its potential users determines the number of final users it will have. This is even more evident for systems that compete with other alternatives, such as transportation systems. Therefore, user-centred design is closely related to the final DRT system's adoption rate. The adoption rate of DRT is one of the key issues leading to its failure. The number of passengers that may switch from existing PT or MIT to DRT depends on the service quality and the ease of interaction with the service. The latter concept refers to the booking of services, which is generally done through a call centre, web, or smartphone application. Because of all the aforementioned, when simulating a DRT operation, the demand intensity must be adapted accordingly and not simply copied from the existing PT or MIT displacements. In addition, by including findings on human behaviour in such simulations, further research could simulate the estimated depth and speed of user transition from their preferred transportation method to the new

DRT solution.

Works such as [156, 8, 134, 120] conclude on the importance of adapting the design, operation, and deployment of DRT solutions to specific user groups. The displacement requirements of potential users should be at the centre of the development of a mobility system. In rural areas, where demand is low, and the gap between users is widening, it is especially crucial to consider their characteristics, such as social and travel patterns and technological skills. However, it would be unrealistic to propose a system that adapts to each and every one of its users. Because of that, user-group research is advisable to determine the best operation for the system. Moreover, we consider hybrid operations that adapt to different user groups in various periods of the day as a potential solution to increase a system's adoption rate.

#### **6.4.2.4 Artificial Intelligence for Rural-DRT**

Regarding rural-DRT research, we can establish a baseline of commonly discussed topics and commonly applied technologies for modelling and simulation. Regarding the latter, most proposals are modelled through mathematical or agent-based approaches. The demand for the system's validation is synthetically generated according to surveys and population, vehicle ownership, and other relevant statistics from the serviced area. The system counts with routing algorithms and insertion heuristics to assign passengers to vehicles and schedule the service. Finally, numerical or agent-based simulations are run according to the modelling, and conclusions about the proposal are drawn.

Recently, rural areas have attracted the interest of artificial intelligence researchers, in order to apply in them the type of techniques which are already being developed for smart cities [91, 140]. Still, there is a noticeable lack of innovation regarding rural-specific transportation. Certain aspects of transportation research, such as autonomous vehicles [121], enjoy a high level of popularity and therefore a high level of articles. For the case of DRT, most of the proposed systems do not implement new algorithms for allocating the demand or scheduling operations. On the contrary, the authors assess the viability of specific proposals. The few improvements for the classic algorithms that have been reviewed present general optimisations and do not consider the characteristics of the rural demand to fur-

ther improve the system. Because of that, we wish to highlight those contributions which innovate regarding research topics.

The works in [55, 24, 106] present unexplored topics which tie their proposals to specific characteristics of the serviced area. These topics are incentive-driven shared mobility, integrated passenger-freight transportation, and volunteer driving programs, respectively. In addition, some authors innovate with the optimisation techniques applied to their systems. In [151], demand anticipation is used to improve the classic insertion heuristic. In [93], the authors propose a dispatch policy based on a threshold of passengers onboard a vehicle. In [18], vehicles are rebalanced based on expected demand. Finally, the authors in [82] employ generally unused techniques for their proposal: DK-means to group stops and a genetic algorithm (global optimisation) combined with simulated annealing (local optimisation) to define the system's operation. These works, regardless of their relevance, bring freshness to the field of research and, as analysed in this paper, follow the line necessary to apply real solutions that work in concrete rural areas.

The DRT paradigm facilitates resource savings and transport adaptability. Hand in hand with artificial intelligence (AI), the potential for improving rural mobility increases considerably. Machine learning and pattern recognition techniques can be used for demand prediction and generation, both historically and in real time. This, in turn, may optimise vehicle deployment and passenger balancing. AI can also identify and group potential customers of a future DRT service according to their social behaviour and travel patterns. Regarding the adoption rate of DRT, AI can be implemented to analyse data about the needs of rural populations and identify ways to increase the demand for transportation services, such as gamification: creating incentives for people to use public transportation or offering discounts to those who carpool. Additionally, as mentioned throughout the paper, heuristic optimisation can improve transportation conditions, identify the best routes, and create more efficient routes that reduce the amount of time and money spent on displacement. There are myriad approaches that can be leveraged to the topic at hand, from agent negotiation to evolutionary computation, and most are worth exploring to build original solutions for a research field in need of innovation.

## 6.5 Conclusions

This survey has reviewed relevant works that assess the viability and potential of improvement that the DRT paradigm can bring to rural mobility. Such a task included the description of transportation problems, the characterisation of DRT, and the enumeration of the techniques that computer science brings to implement and experiment with transportation systems. Both analytical and experimental works have been described and classified. Finally, the open issues of the matter, gathered from the reviewing process, have been discussed.

The main takeaway points of the present work are the following. Practical research needs to be more in touch with its theoretical counterpart. Works that apply the knowledge of transportation research must favour the approaches which are economically viable. The problem of low adoption rate and implementation that does not adapt to the potential users of the rural area has to be considered in every step of the formulation of the transportation system. PT providers must understand those issues and adapt their expected ridership amount accordingly. It is smart to begin with a somewhat less flexible operation and increase the flexibility if factors such as demand justify it. Finally, one should always keep in mind the potential of multimodal transportation; study the application area to try and create partnerships with other actors that facilitate the transition to the new transportation method.

From the point of view of computer science research, there is a need for rural-specific works that use the deployment area's features to find innovative and creative optimisation solutions. There are a series of unexplored algorithms that could bring new perspectives to synthetic data generation, mobility modelling, and simulation.

The present research inspires two logical follow-up works. On the one hand, the results of this work could be applied to the definition of a framework describing the series of steps that both PT providers and researchers in the area should follow when considering the design and implementation of a DRT system, giving the necessary importance to user-centred design, multimodality, and innovation in modelling and optimisation. On the other, we would like to take advantage of the latest advances in AI to study the best way to implement and improve rural-DRT.

Regarding the latter, we have plans to develop a general framework for trans-

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portation fleet optimisation. Employing agent-based modelling to reproduce public transportation and other types of fleets, and integrating different algorithms to optimise aspects such as task allocation and vehicle coordination from both a centralised and a distributed perspective. A few examples of algorithms we have been researching would include insertion heuristics, distributed negotiation and task allocation through auctions, or distributed planning of the fleet's operations[96]. With the aforementioned ideas, a first approach on demand-responsive systems can be found in [101].

Machine learning techniques are also a powerful tool to innovate in the improvement of the operational area and further optimise transportation operations. For instance, in [61] demand-prediction models are developed to test and optimise a public bus service. Finally, we would use massive multi-agent simulation techniques, such as those illustrated in [100], to validate the different systems and identify potential partnerships with other means of transport or actors in the rural area.





# A Flexible Approach for Demand-Responsive Public Transport in Rural Areas

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### **Abstract**

*Rural mobility research has been left aside in favour of urban transportation. Rural areas' low demand, the distance among settlements, and an older population on average make conventional public transportation inefficient and costly. This paper assesses the contribution that on-demand mobility has the potential to make to rural areas. First, demand-responsive transportation is described, and the related literature is reviewed to gather existing system configurations. Next, we describe and implement a proposal and test it on a simulation basis. The results show a clear potential of the demand-responsive mobility paradigm to serve rural demand at an acceptable quality of service. Finally, the results are discussed, and the issues of adoption rate and input data scarcity are addressed.*

## 7.1 Introduction

Demand-responsive transportation (DRT) was first developed in the UK in the 1960s as a means of rural transportation [130] with a flexible route and dial-a-ride program. In the past, it has been utilised to provide on-demand transportation services for those who are physically disabled. These early initiatives depended on government money, and if that funding was cut off, they eventually ceased to exist. In fact, funding has always been a major problem in DRT because, typically, a transportation mode's flexibility results in greater operational costs [30, 42]. Public transportation companies have rekindled their interest in DRT systems in today's environment of dial-a-ride private transportation [57] (taxi, Uber, Cabify) powered by smartphones and applications. The reason is twofold: On the one hand, the technological advancements in computation and electronics make it possible to solve complex problems such as online vehicle scheduling, routing and detouring in brief computational times. Moreover, the popularisation of smartphones has made on-demand mobility more accessible than ever for the newer generations. Finally, the advances in autonomous mobility made demand-responsive transportation more promising. On the other hand, the flexibility and responsiveness of DRT are intuitively good attributes for an environmentally conscious, more sustainable transportation mode that may be able to reduce empty-vehicle displacement, thus reducing energy consumption and greenhouse gas emissions.

The interest of the research community in DRT has been rising in the last few years, although most of the studied and proposed systems are developed for high-density urban areas. In contrast, the application of DRT solutions to rural settlements or areas is less explored. Rural areas count with scattered residents, a low level of transportation demand, and, on average, an older population with respect to urban areas. Its usual transportation methods feature a single line with a mid-to-high capacity vehicle and a low frequency. The lack of quality public transportation is reflected in the usage of individual motorised transport, which is the most popular form of transportation in some rural areas [135]. DRT seems appropriate to fit rural demand and has the potential to cut operating costs while being more sustainable thanks to its on-demand activation. In addition, passenger experience could be improved by lower waiting and riding times.

There are a few works that analyse the potential of DRT for rural mobility.

The authors of [29, 127] propose the replacement of the traditional transportation services of specific rural areas with a DRT alternative. Both works find a better overall efficiency with DRT compared to the fixed service. Particularly, the results in [29] show a decrease in the amount of travelled kilometres, operational costs, and greenhouse gas emissions per passenger. Other analytical works such as [156, 8] focus on the adoption rate of these services among rural inhabitants. Their findings show a potential niche market for DRT transportation and explicit relevant factors that the user takes into account to switch to a new transportation service. Finally, the work in [134] goes over rural DRT services from a customer satisfaction perspective, evidencing a concerning conflict between user expectations and the actual system operation. The authors underscore the importance of the analysis of the rural area and the characterisation of its potential customer needs for a successful DRT application. All the research cited above shows that several authors from different contexts find the use of DRT as a potential solution for improved rural mobility. However, there is a noticeable lack of papers that bring more intelligent techniques to rural mobility.

Urban areas have always had a steady flow of quality proposals, such as [83, 164], focused on optimising their processes. However, rural areas find a clear lack of proposals. Specifically, our current research is motivated by the literature gap regarding the application of intelligent techniques for rural DRT services. The main objective of this line of work is the development of practical solutions for dynamic, flexible, reliable, and economically viable rural mobility. Working on such a goal, this paper characterises DRT systems, assessing each of the challenges their design and implementation implies. Given the specific issues of rural areas, we theorise that the DRT paradigm might be a good fit to provide displacement services to their inhabitants. We prove our hypothesis by describing and implementing a system, which is later tested by simulating its operation in a real rural area. The results show the system achieves a good quality of service over a wide area with a reduced fleet of smaller (with respect to public buses) vehicles. Our work contributes to the rural mobility research field with the introduction of an algorithm that schedules both the static and online operation of the proposed DRT service. In addition, our results show the potential DRT has to modernise and improve rural transportation systems.

This work is an extended version of the paper “Demand-responsive Mobility for

Rural Areas: A Review” [95], presented at the 20<sup>th</sup> International Conference on Practical Applications of Agents and Multiagent Systems (PAAMS 2022). The rest of the paper is structured as follows. Section 7.2 dissects DRT through the review of relevant literature works. Then, Section 7.3 describes the proposed system, its components, and the algorithms that make it work. Section 7.4 presents the use case and the simulation results. Section 7.5 discusses the introduction of DRT to rural areas in accordance with our results. Finally, Section 7.6 concludes the work and states possible future directions for our research.

## 7.2 Demand-Responsive Transportation Description

A DRT system is composed of a series of subsystems, each in charge of solving one of the many challenges a transportation system involves. These subsystems are highly configurable and can be adapted to the concrete mobility needs of a specific area. Because of that, the variety of DRT services is vast. Nevertheless, all of them deal with a concrete set of issues presented below:

- *Planning of services and scheduling of requests.* Whether it is performed in advance or in real-time after receiving transportation requests, a DRT operator must plan the operation of its fleet according to its resources. Depending on the type of system, such planning may include routing and stop assignment. In addition, in a request-based system, passengers must be assigned to a vehicle (or a concrete line) that will serve them. This assignment implies the rescheduling of the vehicle planning to include new customers while worsening as little worse as possible other passengers’ experiences.
- *Optimising fleet resources.* The goal is to select the appropriate vehicles with a concrete capacity such that the operation of the DRT system yields an acceptable quality of service while being economically viable and sustainable.
- *Demand prediction and estimation* can be a complementary feature of DRT systems used to optimise their operation. Such a feature can be implemented based on historical data or prediction techniques to control future and current

demand. Many solutions require the passengers to explicitly state their desire to use the service by issuing a request.

- *Validation* through the definition of appropriated metrics to evaluate and compare different configurations.

Solutions to the above issues are dependent on the concrete type of DRT system that will be implemented in addition to the modelling and optimisation techniques used for that. Following, we describe the different characteristics that a DRT system can have (Section 7.2.1) and the techniques that have been observed in the literature for their implementation (Section 7.2.2). Finally, we enumerate the optimisation perspectives of the reviewed material (Section 7.2.3).

### 7.2.1 System Types

DRT systems have a series of standard elements present in all of them. Different authors apply different labels to those elements. For the current section, we have followed the terminology described in this survey [152].

In a DRT system, a *service* is the departure of a vehicle to serve the transportation requests it has assigned. One service is generally tied to a concrete area or line the transport will follow. In contrast, a *route* is the concrete path the vehicle follows, connecting all the pickups and drop-offs. A route does not necessarily include all existing stops in a line or area. Customers are picked up and dropped off in a predefined set of *stops* within the serviced area or line. Alternatively, a *door-to-door* service can be offered, in which any user-specified location within a particular area may act as a stop. This type of mobility is thought to be *shared*; i.e.: multiple customers are served by the same vehicle. Typical vehicle choices for demand-responsive services include a taxi-like car with a capacity of 4 passengers, vans with 8 to 12 seats, and mini-buses or buses with 16 to 22 seats, respectively.

Many use cases exist for demand-responsive transportation. Specifically, for rural DRT, we find the following: transportation within rural settlements, transportation between rural settlements, and transportation between rural and urban settlements. In practice, these cases can be reduced to two systems: *many-to-many*, with multiple origins and destination locations, and *many-to-one*, where origin and

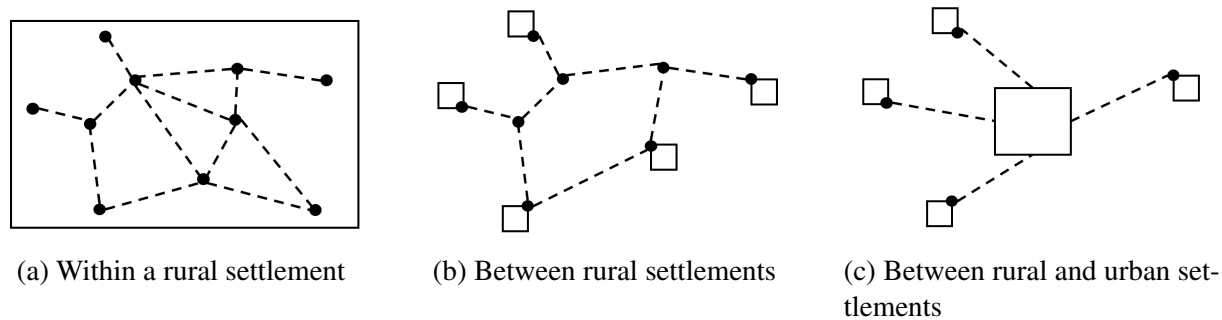


Figure 7.1: Observed use cases for rural demand-responsive transportation systems. Boxes indicate rural/urban settlements. Black dots represent stops. Dashed lines represent demand-responsive lines. Pictures (a) and (b) are cases of many-to-many transportation, while (c) represents a many-to-one model.

destination locations share a unique pick-up or drop-off point. The last type is usually the so-called feeder line, where flexible transportation service is used to move passengers to another, less accessible service (for instance, communications from rural settlements to an airport). Figure 7.1 shows a schematic representation of the commented use cases.

If the customer is required to send a *request* to access transport, then the service is provided *on-demand*. The time between sending a request and the customer's pick up is the *lead time*, and it is used to adapt the fleet operation or *planning* to include such a request. In a stop-based operation, the customer will be assigned a stop from which they will be picked up. On-demand systems can operate based on reservations issued in advance by the users, and in real-time, accepting last-minute bookings. The more complete systems employ a hybrid approach, accepting advanced reservations as well as real-time travelling requests. DRT systems that are not on-demand are also possible. These systems consider current demand or demand predictions for service planning but do not require requests to run.

The period of time for which the DRT service is planned and optimised is referred to as *planning horizon*. The duration of planning horizons is usually a whole day. In addition, the operator may plan for a few hours to adapt to high/low demand periods. According to the influence of the demand data on the service planning, the system will be *fully-flexible* if routes are planned from scratch according to current

demand, or *semi-flexible* if a predetermined plan exists but vehicles are allowed to modify it influenced by demand.

### **7.2.2 Modelling and Optimisation Techniques**

Once the concrete type of DRT system has been chosen, it must be modelled and tested to check its performance and adjust its attributes. We will discuss below the different steps this involves, citing relevant research and their authors' methods. Please be aware that not every paper cited in this section explores rural DRT.

Most rural DRT works are set in a concrete rural settlement or area. In general, the main transportation network (roads, highways) of the area is mirrored thanks to services like OpenStreetMap ([openstreetmap.org](http://openstreetmap.org)) or OpenSourcingRouting-Machine (OSRM, [project-osrm.org](http://project-osrm.org)) [41]. Ideally, the actual organisation of the area, its types of districts, population, or socio-economic reality, among others, should also be considered. Authors in [80] describe a seven-step analysis method for optimising any transportation system based on reproducing the features of the currently implemented transport service (that would potentially be replaced) Alternatively, some works employ grid-like modellings of the area where the system will run [23].

Demand modelling is also crucial. Passenger demand has two main aspects: (1) frequency and intensity and (2) shape (location of origin-destination pairs). Demand attributes can be extracted from datasets of different transportation modes and extrapolated, as in [60], where taxi data is used. Moreover, real data of pilot DRT services [150, 29] can be reproduced when available. However, the most observed technique is the use of synthetic demand data that can be generated statistically [23], based on socio-demographic information [153], via surveys [80, 136, 41] or generated in a (semi-)random [151] way according to the properties of the reproduced area (population, age, occupation, vehicle ownership). Finally, if traffic intensity data is available, it is useful to include it in the model, although not as relevant for rural areas with respect to city-centred studies since the former tend to have lower intensity.

The operation of the DRT system requires automated planning and scheduling of vehicle services. At the same time, these tasks need information on the time and travelled kilometres that a concrete detour would imply, which makes routing



algorithms also necessary. In addition, since it is common to find online systems that accept real-time requests, the computation time for detours and new request insertions must be kept low. The use of multi-modal planning [41] is common to solve the scheduling of vehicle services. Moreover, some simulation platforms, such as MATSim [9] include their own implementations of the algorithms mentioned above. These implementations usually employ (meta)heuristic techniques [153] that optimise vehicle-passenger assignments (insertion heuristics [18], for instance) or vehicle routing in a short computational time. Besides that, other less exploited techniques, such as automated negotiation, could be used to decide assignments from a decentralised perspective [14].

Finally, to observe the system's dynamics and its operation and adjust its attributes, it is necessary to simulate it. This can be performed through mathematical modelling [80] provided detailed data is available. However, a more popular way of achieving this is through multi-agent simulation (MAS). Among the observed choices, we find NetLogo [144], used in [62], the already mentioned MATSim and even custom simulators [117, 41].

### **7.2.3 Optimisation Goals**

The main goal of people transportation services is to supply the displacement needs of its users. Ideally, the operation of the service shall be performed by optimising three factors: (1) the economic viability of the service; (2) the customer's experience (or quality of service); and (3) the sustainability of the service. These three factors are translated into scopes when it comes to transportation research, and thus we can find works that assess one (only operator perspective [93]), or many of them from a multi-objective perspective (passenger and operator perspectives [85]). The optimisation of customer experience implies the reduction of passenger travel times, whereas economic viability is ensured by reducing operational costs. Finally, optimising sustainability requires reducing vehicle travelled kilometres or the total fleet operational time.

The greatest challenge of demand-responsive transportation systems is finding the equilibrium among the factors above to offer a competitively-priced, economically viable, and flexible mobility alternative to private cars and traditional public transportation. For the case of rural DRT, economic viability is especially difficult,

taking into account the relatively low demand.

In this section, DRT research has been dissected by reviewing various works. The enumeration of its many configuration options is crucial to plan the correct system according to the characteristics of the area of application. In addition, knowing how authors model and implement their proposals facilitates future research. Coming up, we introduce a proposal for a dynamic DRT system that aids in improving rural mobility.

### 7.3 System Proposal

We propose an on-demand, stop-based, many-to-many, and fully-dynamic ride-sharing transportation system to give service to rural areas. A fleet of vehicles provides displacement services with a variable capacity. Each vehicle will follow its own itinerary: the list of stops it will visit during its operation, ordered in time. We assume that users of the system issue travel requests through an application. A travel request indicates the location and time window in a simple manner, such as “Pickup at stop A after 8:30, and dropoff at B by 9:00”.

The implementation of our proposal is based on the work in [58]. Our system is managed by a centralised scheduler which allocates each travel request to a vehicle’s itinerary. The scheduler has two modes of operation: (1) offline planning of services and (2) online scheduling of incoming travel requests. In offline operation, the scheduler prepares the fleet’s itineraries for the following service period (i.e., hours, the following day), finding the optimal allocation of bookings (requests issued in advance). In contrast, during service hours, when the fleet is operating, the scheduler works in online mode, listening to incoming requests and allocating them as they are issued. Figure 7.2 presents a schematic representation of the scheduler’s operation, in which the allocation of a request to an itinerary is referred to as a *trip insertion*.

The scheduler allocates the requests to itineraries such that the system-wide objective function is optimised. Such an objective is the minimisation of the fleet’s operational time, thus reducing the operational costs of the whole system.

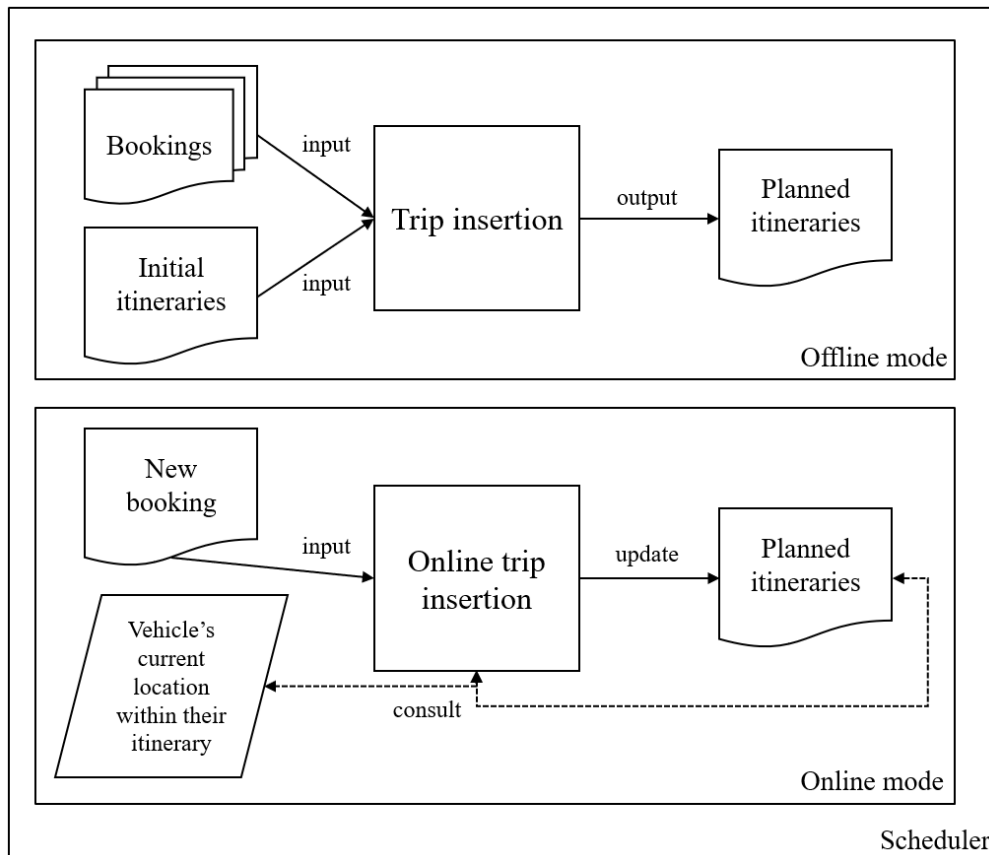


Figure 7.2: Operation modes of the proposed transportation system scheduler. Offline refers to static planning of services, whereas online mode indicates the real-time allocation of incoming travel requests.

Following, we present the system elements together with their attributes and describe the insertion searching procedure that the scheduler implements.

### 7.3.1 Definitions

Before describing the request allocation algorithm, it is necessary to define the system's elements. This section briefly enumerates those elements and attributes, giving important notions to understand our implementation. The time units employed in the following formulation are minutes, as these better serve the purposes of our experimentation.

### **7.3.1.1 Itineraries.**

The fleet is managed by the scheduler, a centralised entity with updated information about each vehicle's itinerary, capacity, and location. An itinerary is equivalent to the vehicle it represents. An itinerary is mainly characterised by its stop list, an ordered list of stops that the vehicle will visit, including the time of arrival to and departure from each of them. Even though an itinerary has additional attributes, we underscore that when the text mentions the insertion of an element in an itinerary, it is referring to the itinerary's stop list, as it can be deduced. The attributes of an itinerary  $I$  are:

- $veh_I$ : Vehicle represented by itinerary  $I$ .
- $cap_I$ : Capacity of  $veh_I$ .
- $I$ 's stop list: List of stops of the itinerary; it has at least two stops.
  - $S_I^{start}$ : Stop where  $veh_I$  begins its shift, including location and time window.
  - $S_I^{end}$ : Stop where  $veh_I$  ends its shift, including location and time window.
- $next_I$ : Next stop of  $veh_I$  within  $I$ 's stop list.
- $cost_I$ : Total amount of time that  $veh_I$  will spend driving to complete the itinerary.

At the beginning of the operation, an itinerary per fleet vehicle is created. The stop list in those itineraries only contains the stop where its vehicle begins its shift and, subsequently, the stop at which finishes it. As travel requests are assigned to vehicles, the stop list of the vehicle's itinerary is updated, inserting new stops in visiting order. Because of that, the stop list represents the route the vehicle will follow to complete its itinerary.

### **7.3.1.2 Trip.**

The scheduler receives travel requests from the system customers. The request is the explicit petition for displacement. Such a petition describes the displacement

in what we call a trip. A trip indicates the need for a certain number of passengers to move from its origin stop to its destination stop. Accepting a request implies that the trip it defines has been inserted in an itinerary, and thus its customers will be serviced. The attributes of a trip  $t$  are:

- $n_{pass_t}$ : Number of passengers travelling as a group on the trip.
- $S_{OR(t)}$ : Pickup stop with location and time window.
- $S_{DEST(t)}$ : Drop-off stop with location and time window.
- $I_{(t)}$ : Itinerary to which the trip is assigned if any.  $I_{(t)} \neq \emptyset$  implies  $S_{OR(t)}, S_{DEST(t)} \in I_{(t)}$ 's stop list.

The time window associated with stop  $S_{OR(t)}$  defines the earliest and latest possible times at which the customers can be picked up. Similarly,  $S_{DEST(t)}$ 's time window defines the earliest and latest drop-off time for the customers. For further clarification on a stop's time window, please refer to the definition of Stops. The wider the time window of a request, the more flexibility the system has to allocate its trip.

### 7.3.1.3 Stops.

A stop represents a physical location within the transportation service infrastructure where customers can board or lay off a vehicle. In our problem formulation, a stop must be part of a trip or an itinerary. Stops have a time window associated with them. The time window indicates to the scheduler the period of time a stop must be serviced, understanding the service of a stop as the service of the passengers associated with it. When part of a trip, a stop  $S$  has the following attributes:

- $t_S^{start}$ : Soonest time at which the stop can be visited by a vehicle. Start of the time window.
- $t_S^{end}$ : Latest time at which the stop can be visited by a vehicle. End of the time window.

- $t_S^{serv}$ : Time employed by a vehicle for passenger pick-up and drop-off at the stop.

In addition, when a stop  $S$  is part of the stop list of itinerary  $I$ , it has the following attributes, which come in handy to check the feasibility of trip insertions. As a reminder,  $veh_I$  indicates the vehicle that follows itinerary  $I$ .

- $t_S^{arrival}$ : Time at which  $veh_I$  arrives to  $S$ .
- $t_S^{departure}$ : Time at which  $veh_I$  departs from  $S$ .
- $w_S^{serv}$ : Service window at  $S$ , indicating the time taken by passengers boarding or laying off  $veh_I$  in  $S$ .
- $w_S^{wait}$ : Waiting window at  $S$ , during which  $veh_I$  waits in  $S$  until the departure time.
- $npass_S$ : Number of passengers boarded in the  $veh_I$  on departure from  $S$ .

Given the above attributes, the time window of a stop is defined as follows:

$$t_S^{start} \leq t_S^{arrival}, [w_S^{serv}], [w_S^{wait}], t_S^{departure} \leq t_S^{end}$$

The vehicle visiting a stop can arrive to it at time  $t_S^{start}$  as the soonest. Then, the service interval  $[w_S^{serv}]$  begins, in which passengers are going on or off the vehicle. Following, the vehicle may wait at the stop for a defined waiting interval  $[w_S^{wait}]$ . At the end of such a waiting period, the vehicle departs from the stop, which may be at time  $t_S^{end}$  at the latest.

The particular arrival and departure times to a stop are determined according to a dispatching strategy. A dispatching strategy defines the use of the so-called slack time, the period of time during which the vehicle does not yet need to leave the stop where it is stationary (represented by  $w_S^{wait}$  in our formulation). A general dispatching strategy would be departing the current stop as soon as possible, providing the earliest possible service to those customers of the following stop. In contrast, other strategies force the vehicle to wait at its current stop as much as possible, hoping new requests will be issued and thus having more stationary

vehicles to assign them to. For this work, we make use of a hybrid strategy. Vehicles will depart from a stop to ensure the earliest feasible service to the following stop. When the vehicle has slack time, it waits at a stop to maximise the chance of inserting an incoming request.

### 7.3.1.4 Insertions.

An insertion indicates the feasibility of allocating the trip of a request to a particular itinerary. Moreover, it indicates the positions within the itinerary's stop list where each trip stop will be inserted. The scheduler looks for all feasible insertions of a trip and implements the best one.

Given a trip  $t$ , its insertion in an itinerary  $I$  implies finding appropriate spots within  $I$ 's stop list to visit  $t$ 's  $S_{OR(t)}$  and  $S_{DEST(t)}$ . The visit to  $S_{DEST(t)}$  must be subsequent (but not necessarily directly after) to that of  $S_{OR(t)}$ . A trip insertion will always increase the itinerary's duration ( $cost_I$ ).

We define a trip insertion  $\pi_{ij}$  with the following attributes:

- $I(\pi)$ : Itinerary in which the trip will be inserted.
- $i$ : Position within  $I$ 's stop list where  $S_{OR}$  will be inserted.
- $j$ : Position within  $I$ 's stop list where  $S_{DEST}$  will be inserted.
- $\Delta_{ij}$ : Time increment incurred by inserting  $\pi$  in  $I$ .

Let us have insertion  $\pi_{ij}$  that allocates trip  $t = \langle S_{OR}, S_{DEST} \rangle$  to itinerary  $I = [S_I^{start}, S_1, \dots, S_n, S_I^{end}]$ . The insertion implies creating two new connections in the itinerary:  $(S_{i-1} \rightarrow S_{OR})$  and  $(S_{j-1} \rightarrow S_{DEST})$ , finally obtaining  $I = [S_I^{start}, S_1, \dots, S_{i-1}, S_{OR}, \dots, S_{j-1}, S_{DEST}, \dots, S_n, S_I^{end}]$ . Keep in mind that we could have  $S_{j-1} = S_{OR}$ , as the destination stop could be visited immediately after the origin stop.

The implementation of a trip insertion modifies the planned operation of the vehicle to whose itinerary the trip is allocated. Such a modification may occur during the reservation-based operation of the system or in real-time while the vehicle is already in service. In the former case, the time windows associated with each

stop in the vehicle's itinerary are updated taking into account the visit to the inserted trip stops. In the latter case, time windows are adjusted in the same manner, but the vehicle may need to change its route to reflect the changes in its itinerary's stop list. Such a change of route, however, will not break the time window of any already scheduled stop, as that is taken into account by our scheduling algorithm (see Insertion feasibility checks, under Section 7.3.2 for further details).

### 7.3.1.5 Cost Computation & Objective Function.

As commented on the definition of an itinerary, its cost is equivalent to the time the vehicle it represents spends travelling throughout its list of stops. Given an itinerary  $I$  with stop list  $= [S_0, S_1, \dots, S_{n-1}, S_n]$ , its  $cost_I$  would be computed by adding the travelling time between every two consecutive stops in its stop list. Let us assume a function  $travelTime(x, y)$ , which, given service stops  $x$  and  $y$ , returns the time taken by a fleet vehicle to travel from  $x$  to  $y$  in minutes. For an itinerary  $I$  with  $n$  stops in its stop list, the cost would be computed as shown in Equation 7.1.

$$(7.1) \quad cost_I = \sum_{i=0}^{n-1} travelTime(S_i, S_{i+1}), \quad \forall S \in I$$

Given a fleet  $F$  of vehicles, the system's objective function is to minimise the total vehicle travel time or distance. This implies direct benefits for both passengers (shorter trips) and the service provider (less operational costs). Such an objective is achieved by the way in which requests are allocated to vehicles. These allocations are done with the insertion search procedure, which works by iteratively finding the best possible insertion for each of the pending requests and implementing it. The search for the best insertion is guided by the cost increment  $\Delta$  that each feasible insertion may incur to an itinerary's cost  $cost_I$ . Therefore, the system's objective function can also be described as the minimisation of the sum of the cost of each itinerary, as represented by Equation 7.2.

$$(7.2) \quad \min(\sum cost_I), \quad \forall I \in F$$



## 7.3.2 Insertion Search Procedures

An insertion search procedure is the action of finding the best position within an itinerary to allocate a request's trip. In other words, the best moment to visit the trip's origin stop and the same for the destination. Our system implements two insertion search procedures, each for an operation mode (online, offline). Following, both procedures are briefly described, together with the system constraints that ensure the consistency of itineraries as trips are inserted.

### 7.3.2.1 Offline Insertion Search.

The offline insertion procedure allocates all bookings to the initially empty itineraries of the fleet. The bookings' trips are inserted one by one, according to issuing time, in the best possible itinerary, i.e., the one that minimises operational time.

The search works as follows: While there are non-allocated requests, the scheduler selects the next request and extracts its trip  $t$ . Given  $t$ , with origin stop  $S_{OR}$  and destination stop  $S_{DEST}$ , we want to obtain all feasible insertions of that trip within all itineraries of the fleet. Algorithm 4 receives the  $S_{OR}$ ,  $S_{DEST}$ , and an itinerary  $I$  with  $N$  stops. Then, it returns all feasible insertions found for trip  $t$  in  $I$ . This is done for all itineraries of the fleet, and all the returned insertions are ordered according to their time increment  $\Delta$ . The scheduler then implements the insertion with a lower  $\Delta$ . The request is rejected if the procedure does not find any feasible insertion.

As it can be seen, Algorithm 4 tries to insert  $S_{OR}$  in every possible position within  $I$ . Once a feasible position is found for  $S_{OR}$ , it is inserted in a copy of  $I$ , and the time windows of other stops are updated, thus creating itinerary  $I'$ . Then, the process tries to insert  $S_{DEST}$  in the position of all stops subsequent to  $S_{OR}$  in  $I'$ . Once a feasible position is found for  $S_{DEST}$ , it is inserted in a copy of  $I'$ , and the time windows of other stops are updated, thus creating itinerary  $I''$ . We have found a feasible insertion at this point, so the algorithm computes its time increment (comparing  $I''$  and  $I$ 's costs) and stores it before continuing the exploration. Please note that  $I'$  and  $I''$  are simply auxiliary itineraries; thus, neither  $I$  nor the stops in  $t$  are modified by the search algorithm. The described procedure constitutes a complete exploration of the possible insertions, allowing the scheduler to implement the optimal one.

---

**Algorithm 4** Search for feasible insertions within an itinerary  $I$

---

**Data:**  $S_{OR}, S_{DEST}, I$

**Result:** All feasible insertions of  $S_{OR}, S_{DEST}$  in  $I$

```

found  $\leftarrow []$ ;          /* List to store feasible insertions */
n  $\leftarrow 0$ ;          /* Pointer to first stop,  $N$  = number of stops in  $I$  */
while  $n < N$  do
     $R \leftarrow I[n]$ ;          /* Select stop in position  $n$  */
    if  $(R \rightarrow S_{OR})$  is feasible then
         $i \leftarrow n + 1$ ;          /* Position to insert  $S_{OR}$  */
         $I' \leftarrow I.insert(S_{OR}, i)$ , recalculate time constraints  $m \leftarrow i$ ; /* Pointer to
             $S_{OR}$  */
        while  $m < N$  do
             $R \leftarrow I[m]$  if  $(R \rightarrow S_{DEST})$  is feasible then
                 $j \leftarrow m + 1$ ;          /* Position to insert  $S_{DEST}$  */
                 $I'' \leftarrow I'.insert(S_{DEST}, j)$ , recalculate time constraints  $\Delta_{ij} \leftarrow cost_{I''} -$ 
                     $cost_I$ ;          /* Increase in duration */
                 $found \leftarrow found + (\pi_{ij}, \Delta_{ij})$ 
            else
                 $m \leftarrow m + 1$ ;          /* Go to next stop */
            end
        end
    else
         $n \leftarrow n + 1$ ;          /* Go to next stop */
    end
end
return found

```

---

### 7.3.2.2 Online Insertion Search.

The online insertion procedure works similarly to the offline one but considers the current position of the vehicles within their itineraries. Therefore, given a trip  $t$  and an itinerary  $I$  being considered for its insertion, assuming  $veh_I$  is travelling the connection  $(R \rightarrow next_I)$ , Algorithm 4 only explores positions within  $[next_I, S_I^{end}[$  for the insertion of the trip's origin and destination stops.

If the trip's origin stop were to be scheduled in  $next_I$ 's position, we would have an immediate request, which implies the rerouting of  $veh_I$ , changing its following stop from  $next_I$  to  $S_{OR}$ .

### 7.3.2.3 Insertion Feasibility Checks.

For the system to work correctly, all itineraries must be consistent. This consistency is enforced through time and capacity constraints.

Let  $S$  be a stop in an itinerary  $I$ . Let  $veh_I$  be the vehicle represented by itinerary  $I$ , with a capacity of  $cap_I$ . Let  $npass_S$  be the number of passengers on board  $veh_I$  on departure from  $S$ . The capacity constraint states that:  $npass_S \leq cap_I, \forall S \in I$ . Simply put, the number of passengers on departure from any of the stops of an itinerary can be, at most, the capacity of the vehicle following such an itinerary.

Concerning time constraints, the system implements the following:

- All passengers must be picked up within the time window specified by their request's start time and the maximum waiting time.
- All passengers must get to their destination before their request's end time.
- All stops must have service windows contained within their arrival and departure.
- All stops must be reached within their time window.

An insertion will be *feasible* if the insertion of its trip in its itinerary does not violate any of the above constraints. The developed insertion search procedure returns only feasible insertions. Because of that, the insertion of a trip in an itinerary will never cause any inconsistencies or constraint violations.

### 7.3.2.4 Computational Complexity.

The presented insertion search procedures perform an exhaustive analysis of every possible position in which to allocate a trip within all the fleet's itineraries. This procedure composes a subproblem of the resolution of the whole DRT service, which will be solved once all travel requests have been dealt with.

Regarding the trip insertion search procedure, its computational complexity depends on the number of stops that the itinerary being explored contains. Such a number of stops, in addition, is generally incremented every time a trip is inserted in the itinerary. This causes the search for trip insertion at the beginning of the operation to be less complex than towards its end. Assuming an itinerary has  $n$  stops, the complexity of the search is of  $\mathcal{O}(n^2)$ , as the algorithm checks each feasible position for the trip's origin stop and, for each of these positions, explores all feasible positions for the destination stop, using two nested loops. In practice, the actual search for an insertion is less costly, as the many restrictions that a feasible insertion has to preserve facilitate early discarding of invalid positions within the stop list.

When it comes to the complexity of solving the scenario, we must take into account that the aforementioned search is performed for every travel request (trip) and every vehicle (itinerary) in the fleet. Thus, the computational complexity of allocating  $T$  trips within  $I$  itineraries is of  $\mathcal{O}(T \times I \times n^2)$ .

As it can be understood, the service schedules travel requests iteratively according to their issuance time, following a FIFO logic. This way of operating is mandatory in the online scheduling of requests, as future demand is unknown. Because of that, the resolution of the proposed DRT service is performed greedily and is sensitive to the order in which requests are fed to the scheduler. To palliate this, improvement procedures could be implemented, which considered global cost optimisations over a solved scenario.

## 7.4 Experimental Results

This section tests the proposed system's potential to satisfy rural mobility demand. For that, we defined simulations that reproduce the system's operation over a concrete rural area. Following, the rural area where the simulations are set is described. Then, the results of various simulations are presented, showing the evolution of the overall service quality of the system according to demand intensity and fleet size.



Figure 7.3: Rural sub-area chosen for the deployment of the proposed system. The area features many small-to-medium-sized settlements. The northern part of the area shows the city of Valencia, Spain.

### 7.4.1 Rural Case Study Description

A rural sub-area of the region of Valencia, Spain, was chosen for the deployment of the demand-responsive service. For that, we departed from the existing public interurban bus service of the Valencian Community, which connects many rural settlements between them and with the region's main cities. The dataset<sup>1</sup>, publicly accessible thanks to the Generalitat Valenciana (<https://linkshortner.net/kkvFj>, accessed on December 15<sup>th</sup>, 2022), contains information on the different

<sup>1</sup><https://dadesobertes.gva.es/va/dataset/gtfs-itineraris-horaris-transport-public-interurba-autobus-comunitat-valenciana>

transportation lines, routes and stops the service offered. Specifically, it describes 722 lines with a total of 4562 stops. From those, only the elements lying inside the area shown in Figure 7.3 were kept. That amounted to 88 lines and 341 stops, shown in Figure 7.4. Since we propose dynamic DRT, the bus lines effectively disappeared, as now vehicles move freely between the stops scheduled in their itinerary. The existing stops, however, were clustered so that any two stops were at least 500 meters apart. With this, the final distribution of 99 stops that can be seen in Figure 7.5 (left) is obtained. With fewer stops and longer distances between them, a better representation of interurban displacement is achieved.

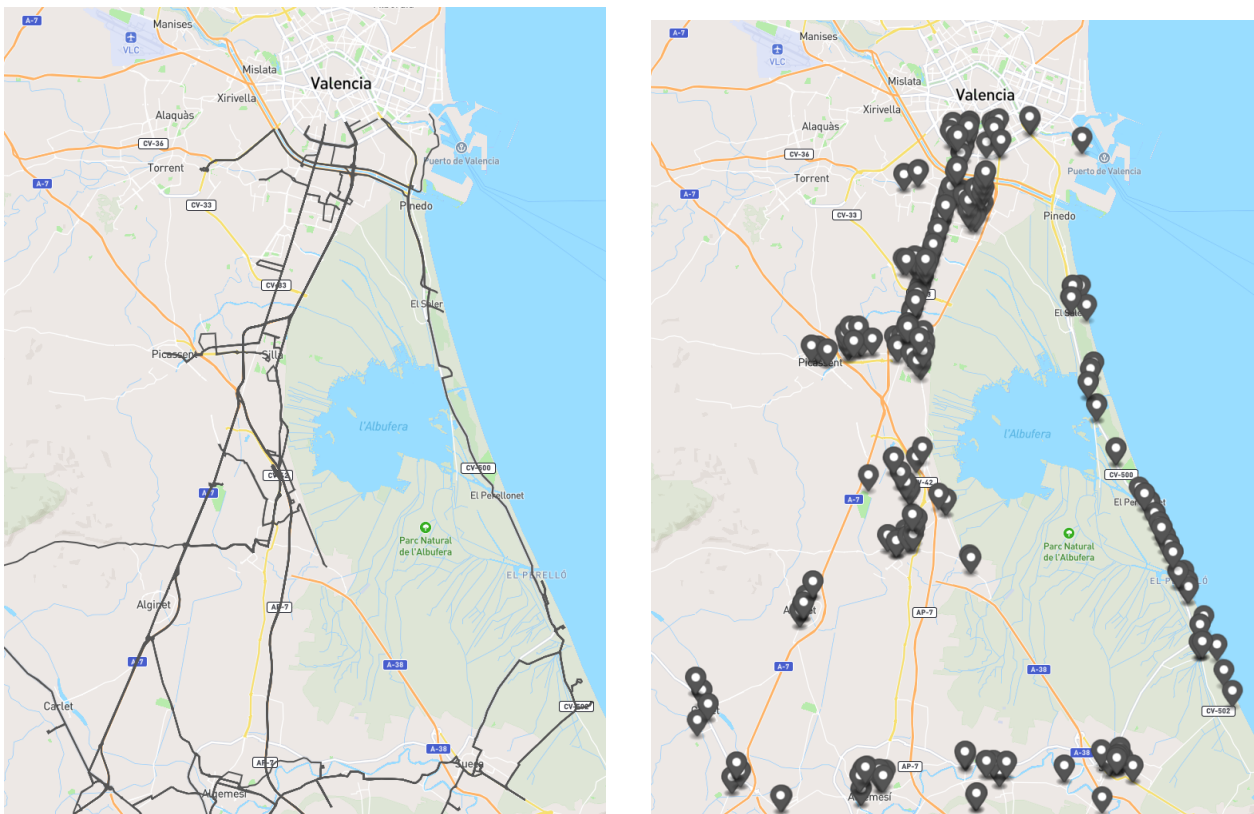


Figure 7.4: Bus lines (left) and stops (right) the public interurban bus service defines in the assessed rural area.

The deployment area features mainly small-to-medium-sized towns located in rural contexts. It can also be noticed how the urban density increases in the northern part of the area, which is closer to the city of Valencia. Our proposal aims to provide on-demand transportation to citizens of the shown settlements, such as

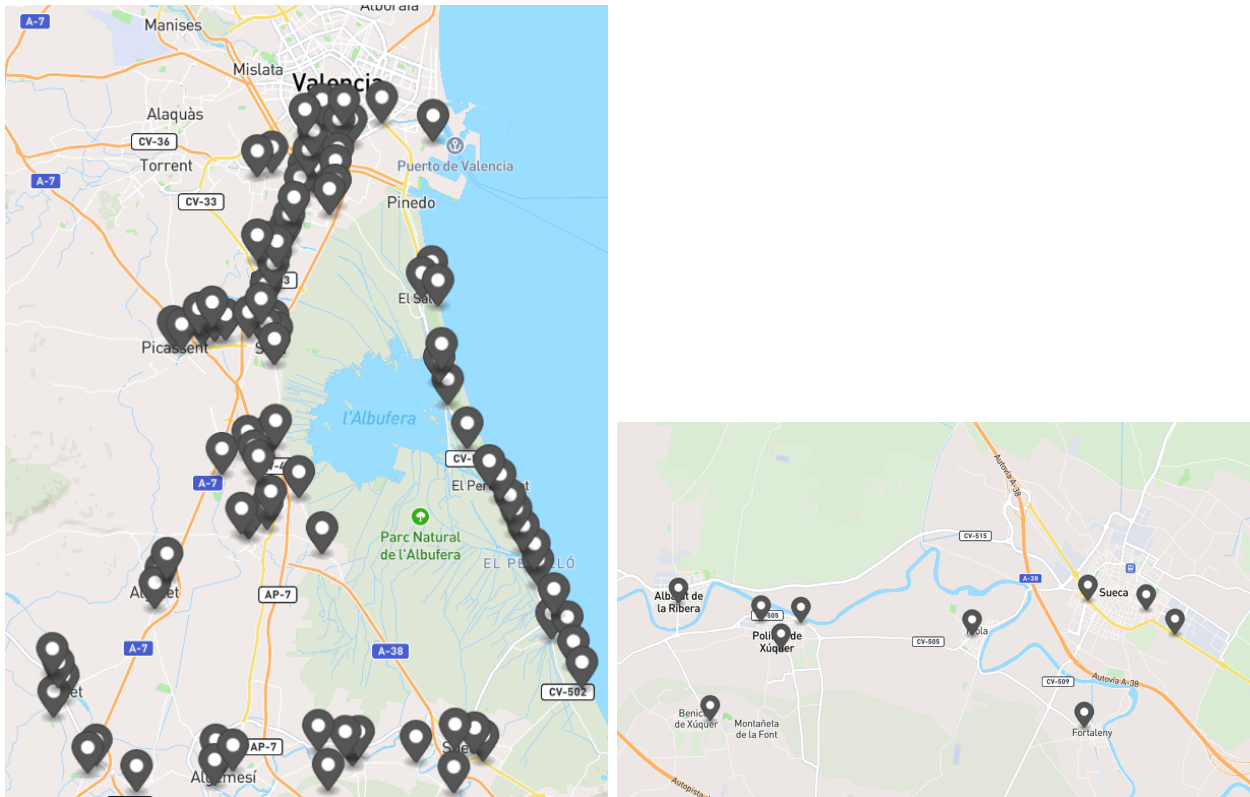


Figure 7.5: Final distribution of 99 stops over the chosen deployment area (left). All stops are at least 500 meters apart. The image on the right shows a close-up view of small settlements in the southeastern part of the area, near the town of Sueca.

Alginet, Algemesí, Silla, Picassent, and El Saler, to mention a few. Figure 7.5 (right) shows a close-up in which the location of stops can be better appreciated. Specifically, it shows the town of Sueca and many smaller settlements nearby.

With respect to the displacement demand, the dataset did not provide usage data. To the best of our knowledge, there is no publicly available usage data for interurban displacement within the chosen region. Rural transportation demand has a lower intensity than that of a city, and given the service area, it tends to be widely distributed in space. With that in mind, a synthetic demand generator was employed to feed data to the simulations.

The demand generator receives geolocated population information of the service area to create demand according to it. The more population nearby a stop, the

more probable it is to be selected as the trip's origin. The destination stop of the request, however, is chosen randomly among all stops, considering a configurable minimum trip distance. Longer trip distances favour the reproduction of interurban displacements. In addition, each request can have between 1 and 5 passengers with respect to given probabilities (less probable the more people). The demand is uniformly distributed throughout the service hours of the system. The end of a request's time window (the time at which the passengers need to be at their destination) is computed according to a chosen maximum waiting time (at a stop to be serviced) and the direct travel time between origin and destination. The direct travel time is multiplied by a configurable factor. The higher this factor, the wider the time window, and thus the more flexibility the system has to serve the request.

### **7.4.2 Service Quality Assessment**

The proposed system has been tested through many 14-hour services (07:00 AM to 09:00 PM) simulations with different amounts of vehicles and travel requests. Inspired by the reviewed literature, a fleet of 10 vans, each with a capacity for eight people, was fixed for the first round of experiments. The vans were deployed from a warehouse in Valencia (the northern part of the service area) at 06:00 AM, an hour before the first requests could be scheduled. Similarly, the drivers had to end their shift at the warehouse no later than 10:00 PM.

With regard to the demand, a total number of travel requests was specified and then generated as described above in Section 7.4.1. The demand is divided into 50% of bookings (scheduled before the system's operation) and another 50% of real-time requests. Each request could have either 1, 2, 3, 4, or 5 passengers with a probability of 0.6, 0.15, 0.125, 0.1, and 0.025, respectively. Finally, a minimum trip distance of 2,000 meters and a maximum waiting time of 15 minutes were chosen. It must be noted that the different probabilities that influence demand generation determine the importance of the subsequent results. For the purposes of demonstrating the proposed algorithm's operation, those probabilities defined above have been used. We remark that the results presented below are dependent on the specific demand generation. Nevertheless, their assessment can give insights to guide future work in this field.



With the fixed fleet of 10 vans, we explored the system's service quality as the number of requests increased. Service quality is defined as the percentage of accepted requests with respect to the total number of requests. In addition, the time that passengers wait for a vehicle to pick them up is included as an additional measurement of service quality. As commented above, for a request to be accepted, their passengers must be picked up before a wait of 15 minutes. Nevertheless, waiting times closer to such a maximum indicate worse passenger experiences. Because of that, our results reflect the average waiting time of all accepted passengers, together with its standard deviation. Table 7.1 shows our first results. The running time of the most complex simulation was 30 seconds, being executed in a machine running Windows 11 with an Intel Core i7-10750H CPU at 2.60GHz and 16GB of memory.

The system maintained near-perfect service quality in runs with 100 to 300 requests (rows 1 to 5). As it can be seen in the last column, given a particular fleet, the system tries to schedule trips so that all vehicles are employed. Only in the first run, with 100 requests, a vehicle is unused. With 350 requests, the system maintains an acceptable service quality with 84.29% of scheduled requests. From 400 requests on, the service quality decays, lowering to 70% with 450 requests and 62.8% with 500 requests. These last three runs present an unacceptable quality of service ( $< 80\%$ ) based on similar works of the literature. With regards to the average waiting times, results show how these increase proportionally to the number of requests. The standard deviation, however, is kept around 5 minutes throughout all executions. This fact reflects the high variability among each of the individual waiting times, which in turn is motivated by the differences among the generated trips. The obtained average times indicate that most of the passengers are picked up relatively soon after the issuance of their travel requests.

#### 7.4.2.1 Fleet Size.

After the initial experimentation, the fleet was varied by adding or subtracting a few vehicles. Once again, the aim was to observe service quality and vehicle usage evolution. For these tests, the number of requests increased from 200 to 500 in 50 request intervals. Table 7.2 presents all the runs. The results indicate that reducing the fleet also reduces the amount of demand the system can appropriately

Table 7.1: Service quality evolution with increasing demand and a fixed fleet of 10 vehicles.

Requests	req/hour	Vehicles	Capacity	Service quality (%)	Avg. pax wait (min)	Fleet usage
100	~8	10	8	100.00	3.5 ± 5.0	9/10
150	~11	10	8	99.33	4.4 ± 5.2	10/10
200	~15	10	8	99.00	4.3 ± 5.1	10/10
250	~18	10	8	96.00	4.8 ± 5.0	10/10
300	~22	10	8	89.67	5.0 ± 4.9	10/10
350	~25	10	8	84.29	5.5 ± 5.3	10/10
400	~29	10	8	74.75	6.1 ± 5.2	10/10
450	~33	10	8	70.00	6.2 ± 5.1	10/10
500	~36	10	8	62.80	6.5 ± 5.3	10/10

manage, as can be expected. Similarly, with a more significant fleet, the quality of service is preserved above the 70% margin for higher intensities of demand. Even in runs with a more extensive fleet, the system achieves a uniform division of requests among vehicles, employing all of them. The pattern of evolution of passenger waiting times is observed to be the same as in the previous experimentation, having standard deviations approaching 5 minutes across all the tested parameter combinations.

The graph on Figure 7.6 visually represents the results of Tables 7.1 and 7.2, showing the evolution of the service quality provided by fleets of various vehicles with respect to an increasing number of requests. Table 7.3 summarises all results, showing the lower bounds of acceptable service quality found for each combination of demand and fleet size.

**7.4.2.2 Vehicle Capacity.**

The final parameter that was assessed was vehicle capacity. The above simulations were run with fleets of 8 to 12 vehicles but changing their capacity to that of a minibus, ranging from 16 to 22 passengers. The results in terms of quality of service, however, were very similar to what has been presented so far. This indicates that, given the shape of the generated demand, vehicle capacity was not a bottleneck of the system, and rejected requests were motivated by time window incompatibilities and not because of capacity constraints. We must acknowledge,

Table 7.2: Service quality evolution with different fleets ranging from 8 to 12 vehicles and various demand intensities.

Requests	req/hour	Vehicles	Capacity	Service quality (%)	Avg. pax wait (min)	Fleet usage
200	~15	8	8	94.50	4.2 ± 5.0	8/8
250	~18	8	8	83.60	5.5 ± 5.1	8/8
300	~22	8	8	76.67	6.3 ± 5.2	8/8
350	~25	8	8	69.43	5.9 ± 5.3	8/8
400	~29	8	8	60.50	6.4 ± 5.1	8/8
450	~33	8	8	56.22	6.5 ± 5.2	8/8
500	~36	8	8	50.60	6.9 ± 5.3	8/8
200	~15	9	8	98.50	4.5 ± 5.3	9/9
250	~18	9	8	92.00	4.8 ± 4.9	9/9
300	~22	9	8	85.00	5.2 ± 4.9	9/9
350	~25	9	8	78.57	5.9 ± 5.3	9/9
400	~29	9	8	69.75	6.2 ± 5.0	9/9
450	~33	9	8	64.00	6.5 ± 5.1	9/9
500	~36	9	8	56.20	6.5 ± 5.2	9/9
200	~15	11	8	99.50	4.2 ± 5.1	11/11
250	~18	11	8	98.00	4.7 ± 5.1	11/11
300	~22	11	8	93.67	4.4 ± 4.9	11/11
350	~25	11	8	89.71	5.1 ± 5.1	11/11
400	~29	11	8	83.25	5.6 ± 5.0	11/11
450	~33	11	8	74.89	6.0 ± 5.0	11/11
500	~36	11	8	67.40	7.0 ± 5.3	11/11
200	~15	12	8	99.50	4.2 ± 5.1	12/12
250	~18	12	8	99.20	4.3 ± 4.9	12/12
300	~22	12	8	97.67	4.3 ± 4.8	12/12
350	~25	12	8	93.43	4.9 ± 5.1	12/12
400	~29	12	8	86.25	5.4 ± 5.0	12/12
450	~33	12	8	80.22	6.1 ± 5.2	12/12
500	~36	12	8	73.80	6.4 ± 5.3	12/12

Table 7.3: Lower bound of acceptable service quality found for all combinations of demand intensity and fleet sizes.

Requests	req/hour	Vehicles	Capacity	Service quality (%)	Avg. pax wait (min)	Fleet usage
250	~18	8	8	83.60	5.5 ± 5.1	8/8
300	~22	9	8	85.00	5.2 ± 4.9	9/9
350	~25	10	8	84.29	5.5 ± 5.3	10/10
400	~29	11	8	83.25	5.6 ± 5.0	11/11
450	~33	12	8	80.22	6.1 ± 5.2	12/12

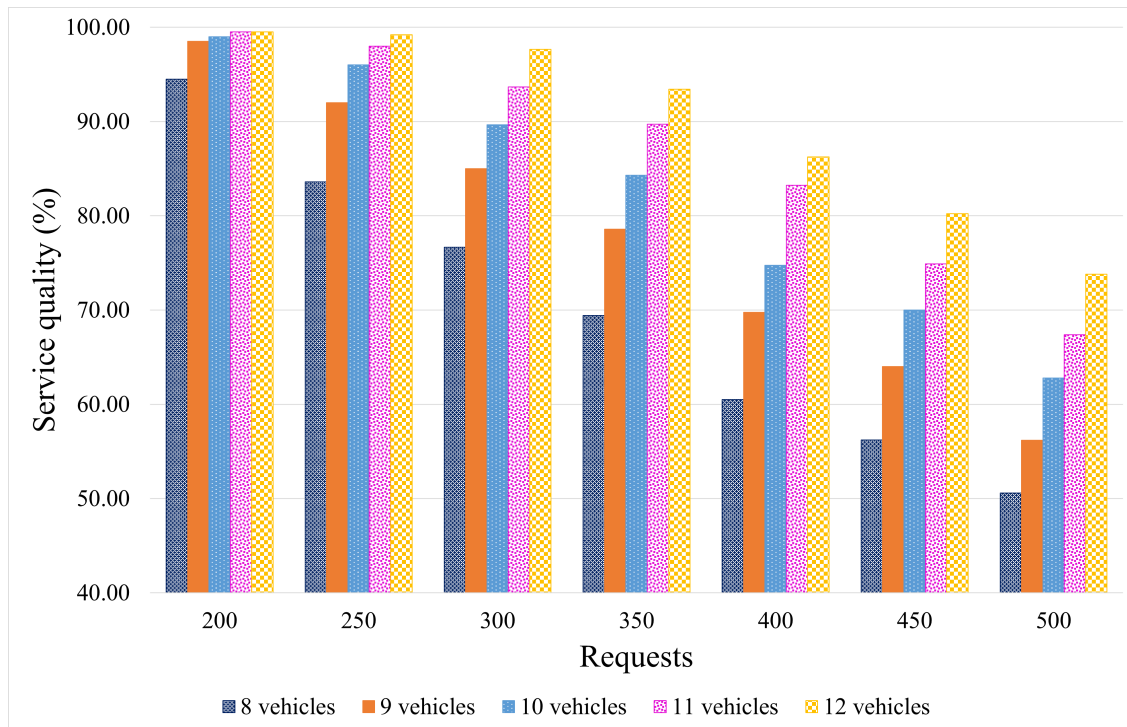


Figure 7.6: Visualisation of service quality according to various number of requests and fleet sizes.

however, that the conclusions drawn from this study of vehicle capacity are only applicable to the specific generated demand. From a general perspective, varying the capacity of fleet vehicles could have a great impact on the system’s performance, which is what motivated this final experimentation.

## 7.5 Discussion

Given the results summarised in Section 7.4.2, we can conclude that dynamic DRT is a good fit for the synthetically generated rural mobility demand. The inefficiency of traditional interurban public mobility options in rural contexts comes from the shape of its demand. Vehicles with a high occupancy ratio, scheduled in periodic lines, tend to drive mostly empty, therefore being costly to maintain for public transport providers. The proposed system tackles these problems by ensuring maximum fleet usage, taking advantage of every present vehicle. In addition,

this behaviour eases the consideration of adding new vehicles to the fleet, as the fleet administrator has the certainty that it will be exploited and thus not a waste of resources.

With regard to the economic viability of the system, having a smaller fleet of smaller vehicles implies lower maintenance and salary expenses. Furthermore, if autonomous mobility becomes feasible in the future, economic expenses would lower even more due to the avoidance of driver salaries. Our experimentation has not explicitly considered the service's environmental impact. Nevertheless, the proposed system has features which indirectly contribute to a better sustainability. On the one hand, the objective function reduced vehicle travel time which, in turn, would reduce any type of emissions stemming from the fleet. In addition, we assess a reduction of such a fleet, achieving a similar level of service quality while cutting costs. Finally, it is worth mentioning that the environment is better preserved because the fleet makes journeys only when necessary. Moreover, these journeys are more cost-effective due to the higher occupancy of the vehicles.

As seen throughout Section 7.2, demand-responsive systems present a high number of operation modes and configurable parts. The present work describes one of the many approaches that could work to modernise and improve rural mobility. Ideally, the proposed system would completely replace the inefficient, traditional transportation options. However, in reality, the adoption rate of DRT tends to be low, even more in rural contexts, due to the necessity to explicit a travel request. The easiest methods to do so consist of smartphone applications and call centres, being the former generally harder to manage for the older population. Because of that, the deployment of a demand-responsive system would initially complement the current mobility options providing, for instance, connection to the most stranded settlements with the main means of public transportation.

Finally, we want to assess the lack of publicly available demand data, which hardens the research on rural mobility. In the context of rural DRT, this issue is aggravated by the lack of rural-specific or low-demand datasets. There are a small number of DRT pilot projects, and among them, an even smaller number share the collected data. Still, the data that can be found about pilot projects is very dependent on the specific area and the socio-demographic context where the pilot took place. To deal with data shortage, synthetic data generation is often employed, basing generation on population, age, occupation, and any other kind of survey that

characterises the potential users of the system.

## **7.6 Conclusion**

In this paper, DRT has been characterised, together with the challenges rural mobility presents for the implementation of efficient modes of public transportation that satisfy the population. A DRT system has been proposed to match the rural mobility demand and provide such a quality service. The system has been described in depth, implemented, and tested by means of simulations. A rural area in the region of Valencia, Spain, has been chosen for the deployment of the system. The mobility demand, in terms of travel requests, has been generated with a synthetic demand generator according to the population of the deployment area and a series of configurable parameters. The research results prove the potential that DRT holds to develop dynamic, reliable, and cost-effective public transportation in the rural context. This research contributes with a system proposal and its validation to the field of rural mobility, which has a general lack of innovation when it comes to displacement proposals.

In terms of future research, we observe two paths. On the one hand, the proposed system can be further improved. Different system configurations must be assessed to find the best match for the deployment area. In addition, the parameters of the proposed system could also be fine-tuned through more experimentation. To further improve results, global optimisation techniques can be implemented in order to further optimise the obtained itineraries. For instance, considering request exchange among vehicles could decrease global costs. Finally, we would like to include transfer operations as an option for the scheduler to allocate requests. These operations have the potential to simplify the fleet operation, cutting costs. On the other hand, regarding experimentation, it would be interesting to assess the impact of different levels of demand dynamism, tighter request time windows, or different dispatching strategies, to mention a few. Finally, simulation results could be enhanced by considering factors such as vehicle autonomy or strategic agent behaviour.

As closing remarks, we want to state that there is a need for specific investigations on the successful implementation of DRT. To bridge such a gap, researchers

must go beyond service quality to focus on the adoption rate and usage of the system. For instance, we believe in the potential pricing policies that could both attract new users to the system and, in addition, influence how they use it to improve the overall quality of service.

**Part V**  
**Discussion**





### Discussion

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This chapter discusses the main contributions that originate from this thesis. The presented work had as its primary objective the improvement of road transportation through the proposal of several resource distribution techniques, including delivery task allocation and passenger-vehicle assignments. Such an objective was divided into three pathways, as laid out in the introduction. Following, the contributions to the first, second and third objectives are presented in Sections 8.1, 8.2, and 8.3, respectively. Finally, Section 8.4 assesses the main challenges encountered during the thesis development and discloses the limitations of our approaches.

#### 8.1 Contributions to Transportation Simulation

The first objective was the proposal of a framework to model and simulate transportation systems, which would allow us to create and execute realistic simulations from which to ground our results. Part II of the thesis groups the works that achieve this objective. Chapter 2 analyses the most utilised simulation software, pointing out the lack of realistic data generation techniques. Its main contributions are two differently purposed data generation algorithms: the *charging stations generator* and the *mobility data generator*. These algorithms, integrated with the SimFleet multi-agent simulator, constituted a vital tool for developing the thesis experimentation.

On the one hand, the charging stations generator has a significant impact with regard to transportation sustainability research. It allows for the dispersal of cru-

cial infrastructure employed by fleets of electric vehicles (EV) and electrically motorised individual transports (MIT). Such a distribution is performed over the area where the simulation will occur through geometry-based methods or data-guided algorithms, such as the genetic algorithm previously developed in works [75, 116]. Even though our thesis centred on road transportation systems and fleets, this generator has had a critical role in enabling transport-related research that focused on charging infrastructure optimisation. On the other hand, the mobility data generator has contributed towards all of our research, allowing us to localise the agents of our simulations according to the real-world data of the area where they took place, whenever possible. In this case, the generation can be based on a probability distribution over the area or regression data computed by a machine learning architecture.

Most of our research results are distilled from assessing simulations. The quality of the simulation directly affects its output data. Chapter 3 demonstrates the usefulness of the generators and their integration with the SimFleet simulator. In that work, we model two different types of urban road transportation: a traditional taxi service and a fleet of carsharing vehicles. The experimentation assesses both fleets regarding operational costs, customer experience and environmental impact. The results gave us key insights regarding transportation improvement research, such as the difficulty of directly comparing two different services and the importance of adapting the service to its potential users. Finally, it is worth underscoring the development of a hybrid simulation in which a reduced taxi fleet was combined with the carsharing service to assess a more realistic urban area where inhabitants have several mobility choices.

All in all, Part II presents our first mature proposals for the modelling and testing of transportation systems. The data generation techniques presented in Chapter 2 pose a practical contribution to the corpora of tools that aid in transportation simulation research. Then, the work developed in Chapter 3 validates the proposed simulation framework, certifying the fulfilment of the first objective.

## 8.2 Contributions to Urban Transportation Enhancement

The second objective of this thesis was the proposal of intelligent solutions for improving urban road transportation through intelligent resource distribution and usage. Part III of the thesis groups the main works that contribute to this objective. The state-of-the-art research on urban transportation systems is analysed in Chapters 4 and 5, but also in Chapter 3 in Part II. Firstly, Chapters 3 and 5 explore different types of urban road transportation services, introducing the challenge of fleet sustainability, thus motivating our enhancement goals. Secondly, Chapter 4 extensively analyses the state-of-the-art artificial intelligence techniques employed for modelling and optimising urban fleets. These include multi-agent systems, fleet coordination through game theory and automated planning.

Part III contributes with two system proposals that tackle different cases of urban transportation. On the one hand, Chapter 4 proposes a last-mile delivery service emphasising its coordination to avoid congestion. On the other hand, Chapter 5 focuses on passenger transportation services, aiming to propose an innovative system that circumvents the issues that traditional services pose.

Chapter 4 contains our most explicit contribution to the redefinition of transportation as a distribution of resources problem. In it, we model an urban delivery service scenario in which the city's road network and charging stations represent shared resources. The vehicles in this scenario develop a congestion game, competing against each other for resources. The more simultaneous usage a resource gets, the more impact it has on the player's costs. This motivates the agents to coordinate their actions, avoiding conflicts and resource congestion. We take advantage of this modelling to improve the delivery time and the sustainability of the service, motivating the drivers to bypass congested roads. In terms of algorithmic proposals, this chapter introduces an optimal planning algorithm that considers the aforementioned resource congestion. In addition, it proposes a practical implementation of the multi-agent coordination algorithm introduced in [73], allowing for its use with fleets of hundreds of vehicles. These two techniques, integrated into the best-response fleet planning process, solve the congestion game that represents the completion of all deliveries.

Regarding the proposal of Chapter 5, we found that demand-responsive shared transportation (DRST) offered a middle ground between the rigidity of public transportation and the pollution and urban congestion caused by private dial-a-ride services. A DRST service has the potential to provide a user-adapted travelling experience, such as taxi services would, but in a shared vehicle, thus having a lower cost and environmental impact per passenger. The proposed dial-a-ride DRST system was serviced by an open fleet of self-interested drivers with the autonomy to choose the request they are more interested in. Conflicts among drivers aiming for the same request are solved through distributed coordination techniques. These features bring unique benefits to the operational costs, service quality and sustainability of the transportation system, which we discuss below.

The publications encompassed in Part III bring a novel approach to transportation enhancement research, particularly with the self-interested modelling of vehicles. Both of the proposed road transportation systems respond to the open issues identified in current urban transportation. The dynamicity of modern cities is matched by orchestrating decentralised transportation services. The decentralised operation makes systems more tolerant and responsive to sudden changes. Open fleets represent the ideal grouping of vehicles for distributed coordination, with each agent retaining the autonomy to select the most beneficial travel requests. These features enable particular improvements concerning service quality and sustainability.

Firstly, the original self-interested driver modelling introduces a unique approach to transportation service quality improvement. Each agent is interested in minimising costs and boosting benefits. Because of that, drivers aim to serve travel requests (whether these are parcel deliveries or passenger displacements) that they can reach as soon as possible. In the case of shared transportation, a driver will be interested in those requests that allow them to deviate from their planned route as little as possible. These characteristics make the system users perceive a tailored service with lower waiting times and swifter displacements. Secondly, the very self-interest of the drivers motivates them to avoid those city resources that other actors are overusing. This results in an operation that reduces resource consumption. Modelling road networks and charging stations as resources, the self-interested drivers plan to avoid dense traffic and the most expensive power prices, lowering the environmental impact of the transportation operation.

### 8.3 Contributions to Rural and Interurban Transportation Enhancement

The third objective of the thesis was the extension and adaptation of the solutions proposed for urban road transportation to the rural and interurban transportation field, with a particular interest in system flexibilisation. Part IV of the thesis groups the publications contributing to this objective. The motivation behind this part came from the observed research gap in innovative road transportation improvement techniques designed exclusively for rural areas. This fact and our results on demand-responsive transportation (DRT) inspired us to study current transportation systems offering rural inhabitants interurban displacement between their settlements.

Chapter 6 reviews state-of-the-art research on flexible and demand-responsive transportation systems. This chapter fully characterises DRT systems, listing their many configuration options and describing how they operate. Then, the relevant publications on the topic are classified into two groups: analyses and surveys, and proposals and experimental works. Articles from the first group were used to gather the main challenges that flexible transportation services face for their successful implementation in rural areas. These include the economic sustainability and adoption rate of the service. The experimental works, on the other hand, were classified by the configuration of the particular DRT system they proposed. Each paper investigated a concrete rural area and its citizens' needs. The analysis of the results gives insight into the type of DRT configurations that operate better in various rural areas.

Our survey on DRT for rural mobility represents a fundamental contribution to rural road transportation enhancement, particularly concerning the proposal of innovative systems and solutions. As evidenced by Chapter 6, there is a small number of publications that deal with this topic. Grouping and analysing them allowed us to understand the social factors that motivate this lack of interest. Moreover, we listed challenges and potentials that different researchers found regarding the few implemented rural DRT services. Finally, our survey lists open issues, aiming to guide future research towards more insightful results.

As a more specific contribution to the contents of the thesis, the findings of

Chapter 6 influenced the type of system that we later proposed in Chapter 7. The contributions described throughout Section 8.2 approached the coordination of transportation fleets from a decentralised perspective, giving a certain level of autonomy to each driver or vehicle. In contrast, the results from our rural DRT survey indicated that an excess of dynamic features ultimately harms rural transportation services. Not only do they increase operational costs, but also the complexity of the user interaction with the service. Although these facts might not be a challenge for urban areas, which count with a generally younger population, it can impede the adoption of DRT services in rural areas. Rural transportation features a high number of MITs coupled with poor investment in quality public transportation and scarce displacement demand. These elements justified a shift towards centralised road transportation systems that could complement existing public transportation while offering a more personalised experience.

Chapter 7 approached the improvement of rural road transportation with a system proposal that minimises travel time, thus reducing operational costs and increasing the swiftness of the service. This chapter proposes an insertion-search algorithm that follows our task distribution modelling approach. Employing it as the scheduler of a demand-responsive service, the algorithm finds the best vehicle to serve each incoming request. The request-vehicle assignments are chosen by the objective function and by considering a time window associated with each request. The preservation of such a time window ensures the reliability of the service, guaranteeing the arrival time of customers who travel with it. The proposal is validated through a case study, localising the service in a real-world rural area and simulating various configurations.

The DRT public transportation system of Chapter 7 recreates a cost-effective quality transportation option designed explicitly with the needs of rural inhabitants in mind. With it, we conclude the work on the third objective, certifying its accomplishment as reflected by Part IV. These contributions towards rural mobility may illustrate demand-responsive services' potential to assemble solutions that overcome rural-specific challenges. The ongoing Spanish research project *Coordinated Intelligent Services for Adaptive Smart Areas* attests to the scientific community's interest in creating intelligent solutions for rural areas. With our work, we contribute to ensuring that the field of transportation does not fall behind all other potential areas of improvement.

## 8.4 Limitations

The proposals developed in the context of this thesis present various limitations, many caused by intrinsic challenges of the road transportation enhancement field. The disclosing of such limitations brings an honest perspective into research and helps the scientific community to be aware of open issues.

Data sourcing remains a considerable impediment to the realistic modelling and simulation of transportation systems. Focusing on urban road transportation, most private companies will keep their data private. Moreover, public transportation data may be hard to find and use, as its maintenance and availability depend on the interest of local government bodies. Concerning rural areas, it is even harder to encounter public datasets that reflect actual mobility data. This challenge shows the relevance of synthetic data generation techniques, such as the ones we presented in Chapter 2.

The results we can derive from simulation are affected by the quality of the data the simulation is based on. Furthermore, when simulating a transportation system, its configuration, constraints and the assumptions we impose during its modelling deeply impact the simulation outcome. These assumptions are generally necessary, as reproducing all and every aspect of a transportation system would require ad-hoc software. As scientists, we must bear this in mind when we draw conclusions from our results. Nevertheless, the assumptions and constraints pay off, as they allow us to experiment with systems that would be costly to modify in the real world. Therefore, the results should not be considered as a step-by-step guide on how to improve a transportation system. However, they can be interpreted by an operator to estimate the potential benefits that a particular technique or system configuration can bring to the studied area. This phenomenon affects the contributions we presented in Chapters 3, 4, 5, and 7, which is why we made it a habit to include discussion sections in our research to help contextualise the results.

In line with the limitations of the simulation results, in the field of transportation enhancement, we find it difficult to generalise the results derived from the experimentation on a specific urban or rural area. Techniques designed for one type of transportation system can often be modified to work with a different one. However, the same cannot be said of the conclusions drawn from a given investigation. Transportation systems are designed and optimised considering the specific fea-



tures of the area they serve or will serve. It is possible to find similarities between different deployment areas and, therefore, use previous results to start experimenting with a system that has the potential to work. Then, such a system shall be refined, re-adapting it to the serviced area and the needs of its potential users.

The next challenge arises from the computational complexity of transportation problems. Transportation systems often require the algorithms that coordinate them to run in real time. Many of the modellings we employed, turning transportation into a resource-allocation problem, implied that our solution space contains multiple combinations of elements. Some of the most powerful optimisation techniques, such as planning, often have pretty high complexities. Because of this, optimal techniques must often be set aside in favour of others that return improved solutions in a reasonable amount of time. This favours the implementation of reactive and demand-driven transportation systems. We take these facts into account in our contributions. Although orchestrated by a distributed coordination algorithm combined with planning, the system in Chapter 4 can solve complex scenarios in a time reasonable enough to organise a fleet of vehicles. In other proposals, such as those of Chapters 5 and 7, the systems have static and dynamic modes of operation. This allows us to accommodate travel requests made in advance in an optimal way. In contrast, requests arriving in real-time are scheduled by faster, often greedy algorithms.

Finally, we want to comment on some limitations of the modelling with self-interested transport agents. As detailed in Chapters 4 and 5, we allow agents to plan their actions according to their private goals. This capability includes showing interest in particular transportation tasks. A specific task may be unattractive to the whole fleet because of its features (location, duration). In such cases, no vehicle would aim to complete it, and the user who issued it would be denied service. This interaction must be considered when using self-interested modelling for real-world applications, including mechanisms that ensure unattractive tasks are still allocated.

**Part VI**

**Conclusions and Future Work**



# Conclusions and Future Work

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The preceding chapters have detailed the aims and development of this thesis and discussed the results. This concluding chapter aims to contextualise the significance of the research findings, underscoring their potential impact on road transportation enhancement and beyond. To begin with, a summary of the work conducted in each part of the thesis is presented. Following, possible future directions of our research are discussed. Firstly, extensions in the field of transportation are assessed. Secondly, we indicate various areas to which our proposals could be applied, emphasising their value as artificial intelligence solutions.

## 9.1 Conclusions

The increasing complexity of modern societies motivates the scientific community to seek intelligent solutions to fundamental problems. One of such problems is road transportation, whose social impact is critical. The presented thesis project had as its primary objective the proposal of solutions for the improvement of road transportation. Such an improvement considers three different points of view concerning the transportation service's operation. The operator perspective prioritises the cost-effectiveness of the service. The user perspective concerns their experience when using the service, usually called service quality. Finally, the sustainability perspective involves the environmental impact of the transportation itself. Integrating three improvement goals in our research has allowed us to produce insightful results.

Road transportation enhancement was approached through the development of computation and artificial intelligence solutions for the task allocation and coordination of these systems. Part of our efforts have been focused on the reproduction and execution of transportation systems in virtual environments. Then, because of the strong relationship of transportation systems to the characteristics of the area in which they operate, our work faced research on urban and rural areas independently.

First, a simulation framework has been developed and validated, subsequently being used to create realistic scenarios for all the experimentation in our research. This contribution includes synthetic data generation algorithms that operate using real information from the area where the transport system will be deployed. The scenarios produced by the generators are coded for its use by the SimFleet simulator, which has been adapted to each specific work, allowing us to extract the relevant metrics.

With regard to urban transportation, previous literature indicated the need for open and dynamic fleets with a greater capacity to react to changes. Moreover, the growing environmental concern justified giving greater importance to the sustainability of the services. We contributed to enhancing road transportation by proposing two differently-purposed systems orchestrated by open, decentralised fleets of self-interested agents. The self-interested modelling was exploited by an urban delivery service whose drivers were motivated to operate faster and more sustainably, avoiding congested roads and lowering power consumption. This proposal was validated by simulating the electric vehicle delivery service in a real city. The fleet vehicles could recharge their batteries in various electric charging stations. If the simultaneous power consumption got past a threshold, the power network would get congested. Tests were run with different numbers of packages, fleet sizes and power congestion costs. The results certified that our coordination algorithm reduced delivery time and proved congestion could be avoided by adjusting its costs. On the other hand, demand-responsive transportation (DRT) supported by shared vehicles was proposed as a sustainable, cost-effective alternative to traditional transportation services, furnishing a responsive system that supplies user-tailored displacements. Our already tested distributed coordination algorithm was applied to organise the operation of a fleet of 8-passenger vehicles. The transportation was performed on-demand, but the service would group travellers with

compatible journeys in the same vehicle. With this, we successfully combined the flexibility of taxis and the sustainability of shared transport into a single service.

Finally, concerning rural interurban transportation, a deep dive into the related publications revealed the need for flexible quality public transportation, underscoring the importance of its cost-effectiveness. The systems and techniques developed for the case of urban transportation were adapted to rural areas' features, orchestrating centralised systems but preserving the principles of dynamicity and sustainability. A DRT system was proposed as a flexible and reliable public transportation alternative for rural settlements. An insertion-search algorithm performed the system's passenger-vehicle pairings, implementing task allocation for minimised travelling time. This proposal was validated by a case study over a real rural area, illustrating the simulation's utility to test various fleet configurations.

## 9.2 Future Work

The objective of this thesis represents an ongoing goal. It has been fulfilled in the scope of the thesis but may continue to be pursued in our future research. Below we discuss possible research directions in various topics. First, extensions to the work carried out in transportation simulation and enhancement are commented. Then, we highlight other application areas to which our solutions could be adapted.

The challenge of data sourcing is an impediment to most transportation enhancement research. In this respect, we believe more powerful techniques should be explored to generate synthetic data consistent with real data. With the help of machine learning, we could build models that learn patterns of demand location and movement of people and vehicles in cities. These models would provide initially acceptable mobility data generation for different cities. However, it would also be possible to re-train them with data specific to the city to be tested, improving their generalisation capacity. This line of work would improve transportation by upgrading its modelling and simulation.

Keeping the focus on the field of transportation simulation, we would like to improve the proposed framework to achieve a multimodal simulation platform. Such a platform would allow us to build scenarios where different modes of transportation systems provide services and interact among them. Throughout the the-

sis, the different chapters have introduced various techniques for the allocation of travel requests to fleet vehicles, the planning of vehicle routes and schedules and, finally, the coordination of the operation of each vehicle. Those techniques, as illustrated by the systems of Chapters 5 and 7, are prepared to work statically, with already known travel demand, but also dynamically, allocating incoming requests. The platform would integrate all of these solutions as building blocks to reproduce a diversity of road transportation services, allowing to test many configurations. In addition, we would also include infrastructure distribution algorithms into the framework, making it a more complete research aid. Ideally, this platform could be adapted to a chosen geographical area where different system configurations could be tested.

Several of the algorithms that we developed for our proposals have the potential to be adapted to application fields beyond transportation. From a general perspective, their purposes are task and resource allocation (Chapters 5 and 7), and agent planning and coordination (Chapter 4). We highlight automated warehouses and smart agriculture crops among the many possible application fields. Multi-agent systems often reproduce these areas, as they have a series of robots that perform various tasks. Automated warehouses perform the movement of inventory with physical robots. On the other hand, in smart agriculture, sensorised robots are being used to check product quality. Both this fields require solutions to model a shared environment, allocate tasks to agents and coordinate their execution.

Beginning with task allocation, Chapters 5 and 7 present passenger-vehicle assignment methods that could be adapted to distribute goals among robots in a centralised or decentralised manner. Such a distribution would be guided by the definition of a global optimisation function. Moreover, these algorithms are designed to operate both statically and dynamically, assigning already determined tasks and dealing with newly received assignments. Adapted to automated warehouses, the algorithms could distribute tasks consisting of the relocation of specific packages to each of the robots in the fleet.

Regarding the coordination of agent execution, the architecture presented in Chapter 4 could be employed in applications with decentralised fleets of robots to distributively coordinate their actions. In addition, if the robots had different purposes, self-interested modelling could be applied, allowing them to choose their tasks through decentralised task allocation. This architecture requires a mechanism

for each agent to plan their actions. Such planning, in turn, implies that each agent needs to estimate data such as the time needed to complete its action. Because of that, we proposed its implementation in a highly connected smart city, where updated information is shared continuously. The elements of this proposal can be adapted to the automated warehouses and smart crops, as the movement of the robots must be coordinated for a safe and efficient completion of their tasks.

Our most recent publications have the digitisation of rural areas as a general goal. The proposals in Part IV contribute to smart rural mobility and are framed in the ongoing research project *Coordinated Intelligent Services for Adaptive Smart Areas* (COSASS). As discussed above, this thesis has produced results that could be applied to the tasks in the COSASS project. Work packages in the project are also interested in techniques for coordinating shared resources. Chapter 4 introduces a modelling of a city as a shared scenario in which agents compete for resources. The planning of each agent's action is guided by their utility function. In turn, such a function considers the usage of resources, thus motivating the agents to avoid their congestion. The principles followed to design such a domain could be adapted to rural smart areas to explore solutions to this challenge.

In conclusion, while aiming at improving road transportation, this thesis project has produced results that can be applied to a number of currently relevant research areas. This emphasises the value of our contributions beyond the field of transportation by contextualising them as practical optimisation techniques in the fields of artificial intelligence and multi-agent systems.





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