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Social Simulation of Mobility as a Service in Closed Communities

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Mestrado Integrado em Engenharia Informática e Computação

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Abstract

Nowadays the number of people that travel to and from different places in urban areas is rising, which makes transportation planning and operation a challenge. With the increasing number of car ownership, moving around a city using private transport is getting increasingly difficult and possibly becoming a less efficient way of moving around.

One emerging mobility concept that can be used as an alternative to tackle this challenge is Mobility-as-a-Service (MaaS). MaaS is a relatively new mobility paradigm with the goal of integrating the various transportation services into a single platform, making use of technology and delivering a mobility service that brings together the end-users and the transportation providers in an almost seamless and sustainable way, focusing on each persons' transportation needs, without having to own a private vehicle. One open issue in this concept concerns the appropriate way to evaluate and measure its efficiency and appropriateness to cope with contemporary mobility performance measures.

Artificial Agent Societies are similar to human societies since they have a number of agents that coexist in a shared environment and pursue their individual goals in the presence of others, interacting with each other in a closed environment with rules. Such a metaphor is therefore presented as a suitable way to characterise the complex nature and interactions of the so-called MaaS systems.

In this work we are considering a closed agent society, which is a social group in which membership is stable and with social interactions between the members. These circumstances make it so that the agents trust more easily in one another as opposed to in an open society.

In societies we have the concept of Social Practices, which are society's accepted ways of doing things between agents in a certain context. They provide structure to social interactions. Examples of social practices are the way we traverse roundabouts, which may differ depending on the country (context) you are in.

This work aims to develop a meta-model for closed communities which, in combination with survey data, is going to be used to generate an artificial agent society so as to allow for an appropriate assessment of MaaS setups. A simulator for MaaS is also going to be developed which takes the artificial society as input with the objective of testing how different incentive policies affect the mobility services used by the agents.

The purpose of this work is to develop a decision-support system platform to assist in the analysis and implementation of incentive policies that would help promote the use of MaaS solutions.

Keywords: Mobility-as-a-Service, Artificial Societies, Social Practices, Closed Community, Simulation

Resumo

Atualmente, o número de pessoas que viajam em áreas urbanas está a aumentar, o que faz com que o planeamento e a operação da rede de transportes seja um desafio. Devido ao aumento do número de proprietários de carro, deslocar-se numa cidade usando transporte privado está a tornar-se cada vez mais difícil e a tornar-se, possivelmente, uma maneira menos eficiente de deslocação.

Um conceito de mobilidade emergente que pode ser utilizado como alternativa para combater este desafio é Mobilidade como Serviço (MaaS). MaaS é um paradigma de mobilidade relativamente recente que tem o objetivo de integrar vários serviços de transporte numa só plataforma, usando tecnologia para entregar um serviço de mobilidade que aproxima os utilizadores finais com os fornecedores de transporte de uma maneira sustentável e harmoniosa. Este paradigma foca-se assim nas necessidades de transporte de cada pessoa, sem que ela tenha de adquirir um transporte privado. Um problema em aberto neste conceito tem a ver com a maneira apropriada de avaliar e medir a eficiência e a adequabilidade para lidar com medidas de performance da mobilidade contemporâneas.

Sociedades Artificiais de Agentes são semelhantes a sociedades humanas visto que têm um número de agentes que coexistem num ambiente partilhado em que cada um persegue os seus objetivos na presença de outros, interagindo uns com os outros num ambiente fechado com regras. Esta metáfora é apresentada com uma maneira adequada de caracterizar a natureza complexa e as interações em sistemas MaaS.

Neste trabalho nós consideramos uma sociedade de agentes fechada. Uma sociedade de agentes fechadas é um grupo social em que os membros pertencentes não mudam com frequência e existem interações sociais entre os membros. Estas circunstâncias fazem com que exista mais confiança entre os membros, ao contrário do que aconteceria numa sociedade aberta.

Em sociedades nós temos o conceito de Práticas Sociais, que são maneiras aceitáveis pela sociedade relativas às interações entre agentes, num determinado contexto. Elas fornecem estrutura para interações sociais. Exemplos de práticas sociais são a maneira como circulamos numa rotunda, que pode mudar dependendo do país (contexto) em que estamos.

Este trabalho tem como objetivo desenvolver um meta-modelo para comunidades fechadas que, em combinação com dados de um inquérito, será usado para gerar um sociedade artificial de agentes, para permitir uma avaliação apropriada de cenários MaaS. Um simulador para MaaS vai ser desenvolvido que recebe a sociedade artificial como *input* com o objetivo de testar como é que diferentes políticas de incentivo afetam os serviços de mobilidade usados pelos agentes.

O objetivo deste trabalho é desenvolver um sistema de apoio à decisão para ajudar na análise e implementação de políticas de incentivo que ajudam a promover o uso de soluções MaaS.

Keywords: Mobilidade como Serviço, Sociedades Artificiais, Práticas Sociais, Comunidades Fechadas, Simulação

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Last but not least,I also wish to thank my friends, with a special thanks to Tiago, for helping me whenever i fell down and needed help to get back up and also for helping me to put things into perspective during stressful times.

Catarina Ferreira

“All our dreams can come true,
if we have the courage to pursue them.”

Walt Disney

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Abbreviations

MaaS	Mobility as a Service
ICT	Information and Communication Technology
PT	Public Transport
TSP	Transport Service Providers
PTA	Public Transport Authorities
FA	Factor Analysis

Chapter 1

Introduction

Nowadays a lot of people use private transportation to travel in urban areas, which creates congestion and makes it so that using private transport is becoming a less efficient way of travelling.

One emerging mobility paradigm that can be used as an alternative to tackle the existent challenge of improving mobility is Mobility as a Service (MaaS).

The rest of this chapter presents the scope of our work followed by our aim and goals and finally a summary of the structure of this document.

1.1 Scope

MaaS is a mobility paradigm with the goal of integrating various transportation services into a single platform. It puts in question the traditional ownership perspective and delivers a mobility service that brings together the end-users and the transportation providers in an almost seamless and sustainable way. Therefore, it focuses on each persons' transportation needs, without having to own a private vehicle.

There are two types of communities in the real world, open and closed. In this work we are focused on closed communities and how we could affect the use of modes of transport, using incentive policies, to motivate users to make more sustainable, cleaner, more efficient and smarter mobility choices.

We use social simulation in order to simulate the relations between the users and observe factors that influence choices regarding the transport mode used for commuting.

Artificial societies are used as a means to represent our population. Some assumptions are made regarding the stakeholders of the society and their interactions.

In our work we will have different simulation scenarios to test how different incentive policies can push towards cleaner and possibly more efficient mobility choices. Extrapolation of the results from this work to the real world is not part of the scope of this project.

1.2 Problem Statement

Our problem is how to promote social awareness in artificial societies as a means to improve system performance measures in domains where agents are mainly pursuing individual, and sometimes concurrent, goals, completely disregarding the performance of the system as a whole. Examples of such domains naturally include urban mobility, for instance.

We want the developed model to be capable of representing the ecosystem of MaaS and all the inherent complexity from this concept, recurring to agent based simulation. Using agent based simulation seems appropriate enough to represent domains as MaaS, facilitating the evaluation of incentives that might promote mobility policies in closed communities towards more sustainable transportation systems.

The model needs to be complex enough to represent the relationships between agents and how different factors influence the choice regarding transportation services.

We hypothesize that social coordination in artificial societies can benefit from more efficient incentives and mechanisms design when exploiting specific properties of closed communities, which we want to demonstrate in this work.

1.3 Aim and Goals

The aim of this project is to develop a social simulation model that could be used to assist in the analysis and implementation of incentive policies that would help promote the use of Mobility-as-a-service solutions. The model would be developed resorting to the metaphors of Artificial Societies and Multi-Agent Systems. The developed model may underline decision support systems and tools, to provide an appropriate understanding of the effects that certain incentive policies can have upon the society.

In order to fulfill the aim of the project we have several goals:

- Develop a meta model to characterize closed communities;
- Analyse response data from survey;
- Create an artificial society based on the analysis' results;
- Rework on HERMES [Cruz et al., 2019] simulator to work as our simulation environment;
- Design incentive policies using the social practices concept to better understand the population and the intricacies behind factors that determine which transportation mode is chosen by the users;
- Define assessment metrics

1.4 Document Structure

Following the introductory chapter, this document contains six additional chapters. Chapter 2 presents the literature review, where important concepts related to this work are analyzed, beginning with Mobility as a Service, existent projects, integration levels, stakeholders, development scenarios and mobility as a service in closed communities, followed by artificial societies, social practices and lastly, incentive policies.

Chapter 3 describes in more detail the proposed approach, by proposing a general view of the work, followed by data requirements, artificial society and detailing the simulation environment. Performance measures to be used in the assessment of our project are also presented.

Chapter 4 focuses on the data used to create the artificial population. It show the origins of the data and the procedures used to analyse it and obtain the necessary data.

In Chapter 5 we present our case study, describe some user characteristics and specify the characteristics of the transportation services while in Chapter 6 we instantiate the proposed methodology and then present and discuss the experimental results obtained from the simulation scenarios.

The document ends in Chapter 7 by presenting the final conclusions of this work and future work.

Chapter 2

Literature Review

The purpose of this chapter is to provide an overview of the areas of study related to the subject of this work, analyzing the concepts in a deeper way to understand them and their purpose for this work.

Firstly, the definition of mobility as a service and various aspects related to it such as development and integration models and also existing projects in different types of communities will be reviewed.

Secondly, artificial societies will be presented, defining the concept and some existent models followed by the concept of social practices and incentive policies.

This chapter concludes with some takeaways from the literature and a gap analysis.

2.1 Mobility-as-a-Service

The concept of Mobility as a Service was first established in 2013–2014 based on the work undertaken by Sonja Heikkilä in Helsinki, Finland [Heikkilä, 2014] and the Go:smart project in Gothenburg, Sweden [ubi, 2013].

In MaaS the service provider would take care of your mobility requirements, while the only choice you would need to make was planning when you would order your ride. All the hassle and costs that come with having a private vehicle would disappear and all your mobility requirements would be easily taken care of with just a look through a platform. [Hietanen, 2014]

2.1.1 The MaaS Concept

MaaS is a relatively new mobility concept that has the potential to become a solution for urban areas suffering from high congestion and poor traffic conditions.

MaaS aims to integrate various forms of transport services into a single mobility service accessible on demand [Mladenović, 2018], where the user's individual transportation needs are taken care of. This mobility solution has the inherent contribution to the goal of decreasing the use of private cars, making it a more environmentally sustainable and aware individual way of transport [Giesecke et al., 2016], substituting the private car for other ways of transportation such as public transport or sharing vehicles.

In the work of Hietanen,[Hietanen, 2014], MaaS is described as a mobility distribution model in which the mobility needs of the customer are met through a single interface offered by a service provider. The author compares MaaS to mobile phone price monthly plans, where various means of transport are combined in a single plan, creating a more tailored mobility package. A different work [Cox, 2015] adds to the previous definition by highlighting the resemblance with the telecommunication sector.

The authors in Holmberg et al. [Holmberg et al., 2016] emphasize a subset of MaaS, Combined Mobility Services, which offer several transportation modes based on subscriptions. Aspects such as giving the users the possibility to plan, book and pay for their whole journey, even if the journey ranges through multiple different transport modes, in a single platform are highlighted.

The objective is that, Mobility-as-a-Service platforms can provide an inter-modal journey planner, combining different means of transportation, a booking system, easy-payment and real time information [Kamargianni et al., 2016] . The users can use the service either "Pay-as-You-Go" or subscribe to a mobility package. With such integration the platforms would provide a seamless door-to-door journey for the users.

The authors in Kamargianni et al. [Kamargianni et al., 2016] name three main elements, which MaaS is based on, that together can provide the users with seamless inter-model journeys. Those elements are Ticket and Payment integration, Mobility Packages and Information and Communication Technology (ICT) integration.

Ticket and Payment Integration refer to only one ticket, physical or digital, being necessary to travel in different modes and only one account is charged for the services. These are normally implemented simultaneously but there still can be special situations where only payment integration or only ticket integration happens. One example where there are both ticket and payment integration is with Andante [and, 2005]. With Andante you can use the train, bus and metro, pay for all the services in only one place (payment integration) and just one card is necessary to access each service (ticket integration).

Mobility Packages allow users to pre-purchase the usage of various modes of transport as if it were one product, like a subscription package more personal to the user. According to authors Simma and Axhausen [Simma and Axhausen, 2001], this type of commitment to one or more specific transport modes reduced the usage of other modes. Since the user's have a long time commitment when buying these packages they will use those modes and can even use them more often, which reduces the usage of other modes. They also found a connection between the use of private transport and public transport. That relation is substitutive rather than complementary.

ICT integration refers to a centralized platform that assembles the information about various modes in order to facilitate and support the users throughout the trip.

2.1.2 Mobility Payment Options

MaaS offers two types of payment options: "Pay-as-you-go" and subscription.

In pay-as-you-go, a trip is organized as if it were a single chain of trips, but the users pay for each part separately, based on the prices set by the correspondent transport provider.

In the subscription model, the users have access to different bundles of transportation services and can have a weekly, monthly or annual fee, based on their needs.

The preference between the two payment models differ amongst the stakeholders. The work of Kamargianni et al., [Kamargianni et al., 2016] studied the opinions of stakeholders in Greater Manchester, UK and in Budapest,Hungary regarding these two options with 54.4% of the stakeholders of Greater Manchester preferring pay-as-you-go while while 70.2% of the stakeholders in Budapest preferred the subscription model.

2.1.3 Current MaaS Projects

Table 2.1 presents some MaaS schemes that have been implemented across Europe and which of the main elements previously identified do they implement.

Most of the projects presented have Ticket and Payment integration and ICT integration but only three have the Mobility Package Integration element.

All of them have integration between urban public transport and the other modes.That integration can affect the environment in a negative or a positive way, depending on the design of the platform [Holmberg et al., 2016]. What can happen is that, if wrongly designed, MaaS can have a negative impact in the environment, such as making public transport users use their private vehicle more. Nevertheless it can also make active car owners exchange their car for a greener alternative.

Regarding existent MaaS projects, one which is mentioned often is the UbiGo project. This project was test from 2013-14 in Gothenburg,Sweden and involved around 200 participants from private households [König et al., 2016]. This service enabled families to buy prepaid bundles of services such as public transport, taxi, rental cars, bike sharing and car sharing. This household subscription could be modified on a monthly basis.

The results from the project were very promising. The participants used their private car less then before, switching it to more sustainable methods such as public transportation, walking and cycling. They also felt more negative towards private cars and more positive towards public transportation etc. [Sochor et al., 2014]

The SMILE Project in Austria aimed to include public transport, urban mobility services and the national railway with the ability of planning, booking and purchasing tickets all in the same app, but without including subscriptions or packages. Unfortunately the turnover from the pilot was very low in comparison with the UbiGo project, which can indicate that the subscription packages are an important aspect.

Another interesting project, operational since 2016, is the Whim project which started in Helsinki,Finland but has since expanded. Whim users can currently choose between 3 types of subscriptions plans. Those bundles present a lot of different services, even having unlimited access to public transport and taxis [Harms et al., 2018].

Table 2.1 illustrates some projects and their level of integration. In table 2.1, besides the MaaS schemes found in [Kamargianni et al., 2016] we also added Andante

Table 2.1: MaaS Schemes information. Adapted from [Kamargianni et al., 2016]

Scheme	Area	Integration Type*				Modes
		1	2	3	4	
STIB + Cambio	Brussels	X				car-sharing, rail, urban public transport, taxi
Qixxit	Germany			X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi + flight, coach
Moovel	Germany		X	X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi
Switchh	Hamburg	X		X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi + ferry
Andante	Porto	X	X	X		rail,urban public transport
Hannovermobil	Hannover	X	X	X		car-sharing, car rental, rail, urban public transport, taxi
EMMA	Montpellier	X	X	X		bike-sharing, car-sharing, rail, urban public transport
Mobility Mixx	Netherlands	X	X	X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi
NS-Business Card	Netherlands	X	X	X		bike-sharing, car rental, rail, urban public transport, taxi
Radiuz Total Mobility	Netherlands	X	X	X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi
Smile**	Vienna	X	X	X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi
Optimod' Lyon**	Lyon	X	X	X		bike-sharing, car-sharing, car rental, rail, urban public transport, taxi + flight, freight transport
BeMobility**	Berlin	X	X	X		bike-sharing, car-sharing, rail, urban public transport, taxi
SHIFT	Las Vegas	X	X	X	X	bike-sharing, car-sharing, car rental, urban public transport
Ubigo	Gothenburg	X	X	X	X	bike-sharing, car-sharing, car rental, urban public transport
Helsinki Model**	Helsinki	X	X	X	X	bike-sharing, car-sharing, car rental, rail, urban public transport, taxi+ on demand transport

* 1: Ticket integration, 2: Payment integration, 3: ICT integration, 4: Mobility packages integration
**In research phase.

2.1.4 Integration in MaaS

MaaS is a mobility paradigm focused on improving operational, informational and transactional integration of transport systems in order to provide the user with a seamless and convenient experience that rivals that of a private vehicle [Lyons et al., 2019].

MaaS platforms have different levels of integration. The higher the level, less effort it takes to the user and the easier the experience proportioned.

Figure 2.1 illustrates a possible taxonomy for MaaS integration levels.

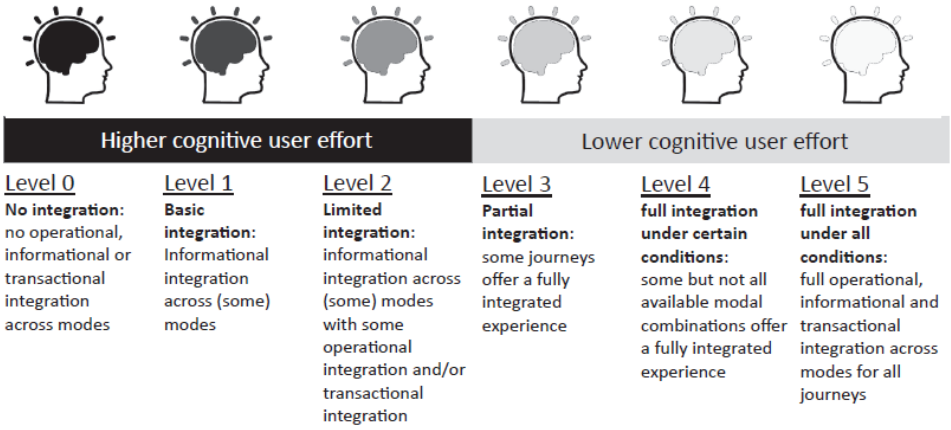


Figure 2.1: Levels of MaaS Integration. Adapted from [Lyons et al., 2019]

Operational integration means that vehicles or lines changes in the journey are seamless. [Lyons et al., 2019]

Informational integration means that planning and execution information the offered modes is available through one interface. [Lyons et al., 2019]

Transactional integration means payment and anything related to booking or ticketing is available through one interface. [Lyons et al., 2019]

Cognitive User effort is the effort the user experiences to fulfill their mobility requirements without relying on their private car. In the figure we can see that the first three levels of integration have a higher cognitive user effort since there is limited to no integration on the platform. That means that the users are responsible for searching for information, planning and payment in a lot of different places instead of it being all available in one single place.

2.1.5 The MaaS Ecosystem

Mobility-as-a-Service is a mobility paradigm change not only for the customer but for the transportation system as a whole, for all the involved parties making so that the boundaries between the different transportation modes disappear or, at least, become more blurry.

In the past, the performance of the transportation system was evaluated on speed, convenience and affordability [Hietanen, 2014] but now, in a more modern world, the way to improve this system is no longer by building more capacity but instead to use what we have available but in a smarter way.

In this section we will describe the stakeholders existent in MaaS and also possible transport operator models.

2.1.5.1 Stakeholders

The authors Kamargianni and Matyas, [Kamargianni and Matyas, 2017], suggest that in order to achieve a co-operative interconnected single transport market to provide the users the hassle free mobility everyone desires, a new participant named MaaS Provider needs to enter the transport market.

The MaaS Provider is an intermediate between the transport operators and the users. It aggregates the transport service providers data into a single platform, buys capacity from the transport operators and resells it to the users. The users then access the platform to plan their trip. However the authors of Smith et al., [Smith et al., 2018] argue that not one but two new participants should be added, MaaS Integrators and MaaS Operators. MaaS Integrators mediate the offers from several transport providers to the MaaS Operators through activities such as contract management, while the MaaS Operators are the ones responsible for delivering MaaS solutions to the end-users by enabling the users to plan their journey and pay for it in a single platform. The concepts of MaaS Operator and MaaS Provider are very similar.

Figure 2.2 represents how the core roles interact in the current transport system and compares it with the integration of the new MaaS participants, MaaS Integrators and MaaS Operators.

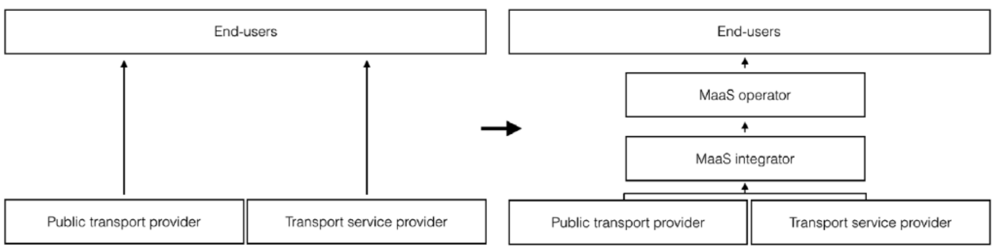


Figure 2.2: Core roles in current framework (Left) and integrated with MaaS (Right) . Adapted from [Smith et al., 2018]

The ecosystem illustrated on Figure 2.3, illustrates the entities involved according to authors Kamargianni and Matyas, [Kamargianni and Matyas, 2017], like MaaS provider, data providers, transport operators, customers, technical solutions and infrastructure (example ticketing and payment solutions, journey planners and ICT infrastructure)

The MaaS ecosystem. described in Figure 2.3, has a number of layers , each of which correspond to different levels of relation to the MaaS Provider.

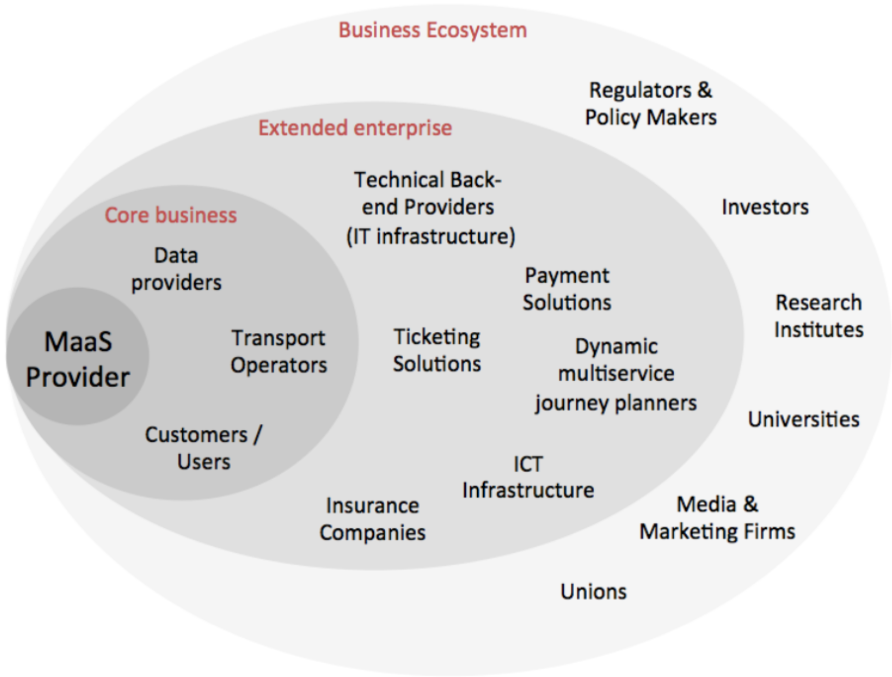


Figure 2.3: MaaS Ecosystem. Adapted from [Kamargianni and Matyas, 2017]

The core business, which is the most central and important part, consists of the MaaS Provider accompanied by the business suppliers and customers, which are the transport operators, users and data providers.

The next layers, especially the last one, widen the view of the business supply-chain by adding actors that may not be directly involved in the operation and implementation of MaaS solutions but still may have a considerable effect on the success of the MaaS model. [Kamargianni and Matyas, 2017]

Table 2.2 explains in more detail some of the stakeholders' roles in the MaaS model.

2.1.5.2 Operators Model

In regards to the MaaS Operator, there are four different models, which are the Public transport operator, Public Private Partnership, Commercial Reseller and Commercial Integrator.

A Reseller offers mobility services of multiple modes of transportation to the users, via one platform.

The Integrator model adds to the reseller model by incorporating a mobile service provider that provides mobile ticketing and payment integration. MaaS may be either the main business for the integrator or just complementary to their service offerings.

Public transport operators can act as MaaS operators by integrating additional transport services such as carpooling and taxis, and digital services with their existing public transport.

In the Public Private Partnership (PPP), the public operator may incorporate different services as a means to enhance the services provided to the travelers [König et al., 2016]. This model can

Stakeholder	Role
Transport Operator/Provider	These are the suppliers to the MaaS Operator. They provide information such as schedule, booking, vehicle and fares to the MaaS Operator.
MaaS Operator	Responsible for combining various existent transportation services and present them to the Users in a single platform, providing personalised transport plans tailored to the user's needs. Responsible for providing the user with a smooth and enjoyable experience.
Users	These are the end-users. MaaS is designed to make transportation more flexible, easier and more sustainable for the users.
Regulators and Policy Makers	These actors have an important role as enablers of MaaS, they should facilitate routes with seamless transfer. They could provide policy frameworks and recommendations for the sustainable development of the market, financing, passenger rights, privacy, security, and safety. They monitor the performance of the market, keeping user's interest in mind.
Technology Providers	Provides technology and services such as ticketing and payment to the MaaS Operator and Transport Providers.

Table 2.2: Stakeholders in the MaaS ecosystem. Adapted from [Kamargianni and Matyas, 2017] and [König et al., 2016]

be a good fit for rural areas where the public actors' main objective is not profits but the increase of the efficiency of subsidized transportation, helping with social inclusion.

2.1.6 Development scenarios

In Figure 2.2 we saw how the two roles of MaaS Integrator and MaaS Operator could be incorporated with the exist roles in the transportation sector.

In this section we will see 3 possible scenarios of implementation of MaaS, according to the authors in Smith et al. [Smith et al., 2018]. These scenarios are Market-driven development, Public-controlled development and Public-private development.

2.1.6.1 Market-driven development

This development scenario implies that both the MaaS Integrator and Operator roles are absorbed by the private sector such as Transport service providers.

The Public Transport Authorities, besides having the duties they already have, have to make it possible so that third-party actors can resell public transport tickets [Li and Voege, 2017], modify the range of public transport tickets to simplify bundling with other services [Holmberg et al., 2016], and offer fair deals to the third-party ticket re-sellers (MaaS Operator).

The Public sector, while still needing to invest in internal technological and business development to be able to make the PT tickets available for resale, acts as an enabler in this development scenario and the private actors are the ones supposed to push the development.

An assumption for this scenario is that MaaS constitutes a reasonable business opportunity for the involved actors such as MaaS Integrators, Operators and TSPs. An argument for the feasibility of this scenario is that private sector actors have both higher incentives and better capabilities to develop the services needed to meet the users' transportation needs in comparison with the public sector.

This scenario is illustrated on Figure 2.4.

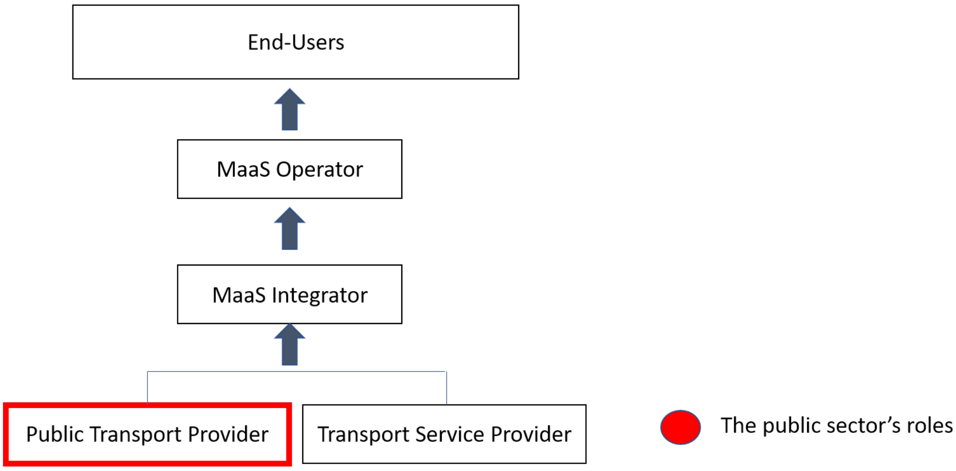


Figure 2.4: Market-driven development of MaaS. Adapted from [Smith et al., 2018]

2.1.6.2 Public-controlled development

This development scenario assigns the MaaS Integrator and MaaS Operator Roles to the PTA which means that the public sector would be the driving force, responsible for the development, implementation and operation of MaaS.

The main purpose behind the development of MaaS is to contribute to a more sustainable way of travel by facilitating the shift from private transport to more sustainable modes of transport, decreasing the use of private cars [Giesecke et al., 2016].

Furthermore PT is the cornerstone to MaaS, being the the only alternative to the use of individual private transport, capable of meeting citizens' mobility needs and using minimum space. During peak hours, high capacity public transport services are the only viable solution to move users [UITP, 2016].

Finally, private and public actors may have different, conflicting goals. While a private MaaS Operator may want to maximize its revenue by selling as many and as expensive trips as it can, the public sector aims to reduce the amount of travel and increase the share of PT, which is a more inexpensive travelling alternative in comparison with car rentals [Smith et al., 2018]. Others also state that adopting these new roles of MaaS Integrator and MaaS Operator may be an unpractical business opportunity since the margins are small within the personal transport sector, large administration costs and the lack of proof end-users' demand for the service[Smith et al., 2017].

This scenario is illustrated on Figure 2.5.

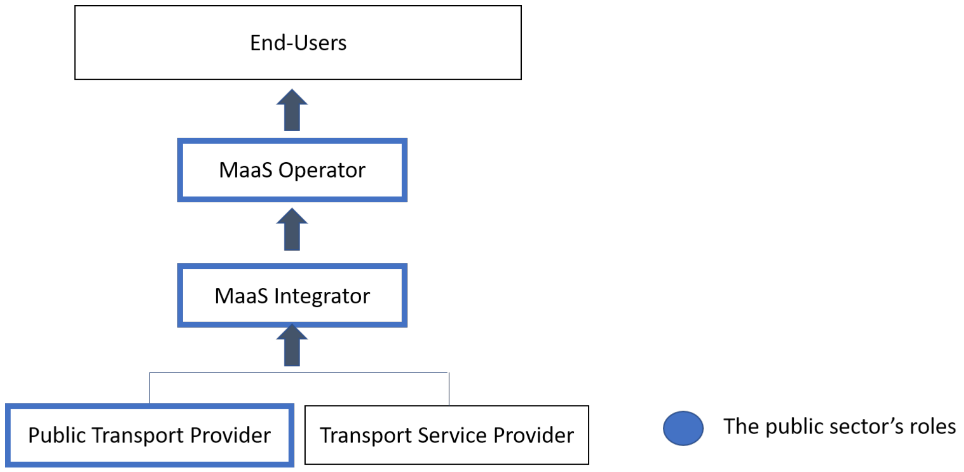


Figure 2.5: Public-controlled development of MaaS. Adapted from [Smith et al., 2018]

2.1.6.3 Public-private development

This is the third and final development scenario, being a halfway between the two previous scenarios, market driven and public driven.

In this scenario the public sector absorbs the MaaS Integrator role while the MaaS Operator role is adopted by private actors, as illustrated in Figure 2.6. This means that both sectors have an active in the development of MaaS.

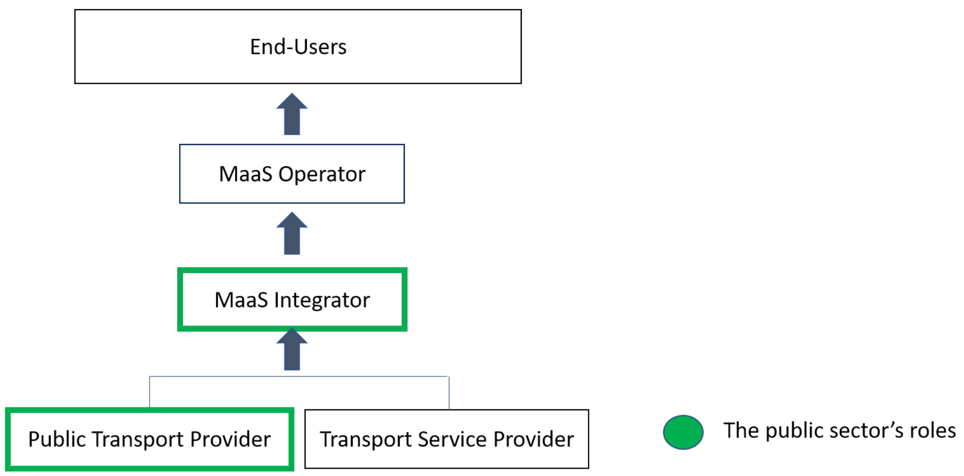


Figure 2.6: Public-private development of MaaS. Adapted from [Smith et al., 2018]

The public sector, contributes to the development by taking on the MaaS integrator role and also taking the actions described in the market driven scenario 2.1.6.1, to enable the private actors.

This can facilitate the integration for the MaaS Operators, technically and contract-wise, since it would lower the initial investment cost.

Furthermore a public controlled MaaS Integrator could mitigate the risks of MaaS Operator becoming too dominant. This could potentially be a measure to avoid situations where MaaS Operators use their position to negotiate unjust business deals (high resale commissions).

2.1.7 MaaS Service Combinations

MaaS is a solution to solve mobility challenges both in urban areas but also in rural areas. It can first be tested in more densely inhabited regions and than use what was learned and apply it to more remote areas.

The impact of MaaS differs from each region, while in urban areas it can improve the quality and efficiency of the transport system, improving traffic, in rural areas, which are more deserted with an elderly population and limited public transport offers, it can help with social inclusion and quality of life [Barreto et al., 2018].

In this section we will describe MaaS in urban, suburban and rural areas and the service combinations in each area. We will also explore service combinations but in a greater scale with it being national and international. Service combinations are analysed through value proposition, value creation system and revenue model.

2.1.7.1 MaaS in Urban Areas

Cities are going to be the first places where MaaS is going to be implemented due to them being densely inhabited areas with a lot of different transport modes, as mentioned previously. With so many different modes, some service combinations already exist but new ones can also be implemented and tested. Figure 2.7 illustrates MaaS services in urban areas.

The goal for MaaS in these areas is to reduce the use of private cars as much as possible. Consequently that will reduce traffic congestion, emissions and also parking issues. The way to reach this goal is to include all or at least most the available transport modes in the service coverage like car sharing, bike sharing, buses and subway [König et al., 2016].

MaaS services can be offered to both private (B2C) and company employees(B2B) which would enable different revenue models for the MaaS operators.

Regarding the different revenue models we would have the most basic one for each trip, which would be pay per usage, the monthly commuter package or an even more customizable monthly package, the all-in-one package.

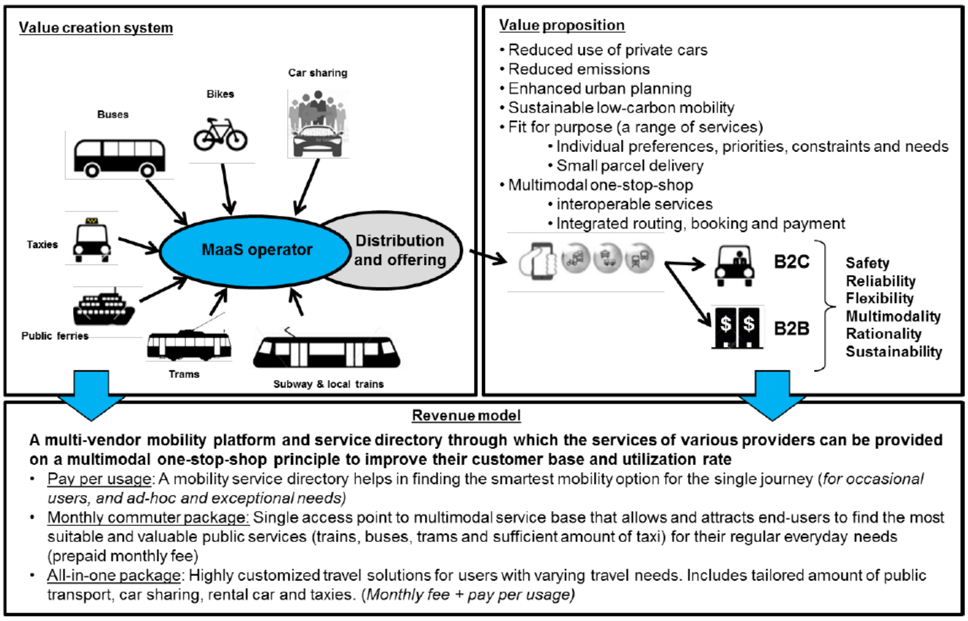


Figure 2.7: MaaS services in urban areas. Adapted from [König et al., 2016]

2.1.7.2 MaaS in Suburban Areas

Suburban areas are areas near the city but outside it, which are inhabited manly by families. Since public transport in these areas is more limited, in comparison with the urban areas, MaaS is expected to improve the service levels by integrating demand-responsive transport like taxis with the available public transport. [König et al., 2016]

With the proper platforms, these are potential locations for carpooling and ride sharing. Figure 2.8 represents MaaS services in Suburban areas.

Since families and other inhabitants of these areas have transportation requirements that may vary a lot, eliminating the use of a private car is impossible but we could eliminate the need for a second car.

Regarding payment plans the one that seems the most obvious, when taking into consideration the varied needs of transport, would be pay per use. Monthly plans could also be an interesting choice depending on the customizability and cost.

2.1.7.3 MaaS in Rural Areas

Until now we have been emphasizing the advantages MaaS would bring to the Urban and Suburban areas, but we must not forget about the Rural Areas since 28% of population, in the European Union [Perpiña Castillo et al., 2019], are still living in the countryside and rural areas.

These areas are suffering from a lack of connections to long-haul and scheduled services and therefore MaaS services might provide significant benefits and it could increase the use rates. [König et al., 2016]. Figure 2.9 represents MaaS services in Suburban areas.

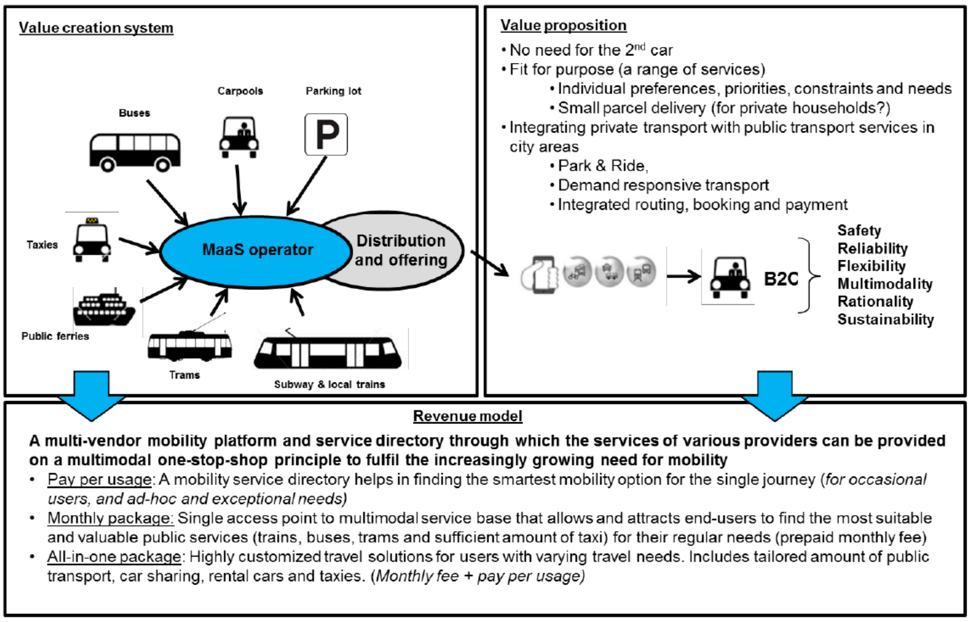


Figure 2.8: MaaS services in suburban areas. Adapted from [König et al., 2016]

Since the demand in these areas can be hard to predict, the most common payment plan would be the pay per use.

2.1.7.4 MaaS on National and International Levels

MaaS services at these levels are related to long-haul travel, whether it be work or leisure related, which means that air traffic becomes an essential part of the MaaS service [König et al., 2016].

These long distance travels are the means to reach a destination, so they are usually associated with other types of services, which is much different than what we have seen in the previous sections. These additional services can include accommodation, tours, leisure activities etc.

Creating this type of long haul MaaS requires the collaboration between multiple operators from different fields, since its a much greater scale. Since no real cases at this scale exist, as of now, we wo not speculate about payment plans. Figure 2.10 illustrates MaaS on National and International levels.

2.1.8 MaaS for Closed Communities

In the previous Section2.1.7 we discussed MaaS in different regions such as urban, suburban and rural areas and also on national and international levels. What all these regions have in common is that they do not differentiate between the users, MaaS solutions being open to everyone. In this section we will explore MaaS in a different setting, Closed Community. We will begin by defining what is a closed community and how it is different from the areas discussed before, followed by some examples of works that explored MaaS solutions in closed societies.

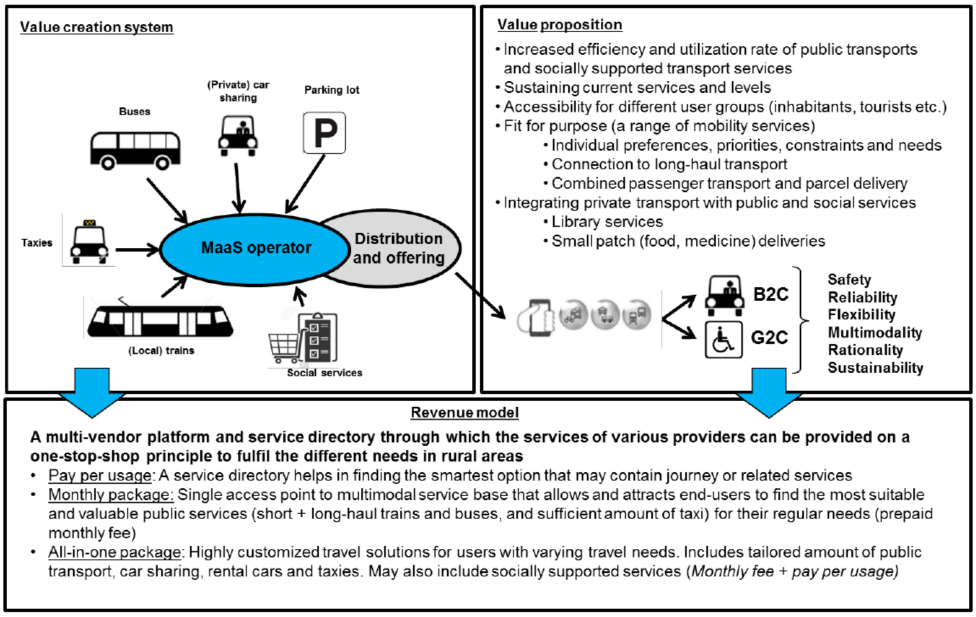


Figure 2.9: MaaS services in rural areas. Adapted from [König et al., 2016]

A society is composed of a large group of people that coexist in a shared environment, who pursue their individual goals in the presence of others, interacting with each other through the environment. The behaviour of the people is constrained by certain rules known as social laws or norms which provide guidelines to how the person must act [HORLING and LESSER, 2004].

A human society can be modeled using the metaphor of an agent society, where the people are agents.

Davidsson in his work [Davidsson, 2001] claims an agent society has certain characteristics such as:

- openness, which represents the possibilities for agents to join the society;
- flexibility, how restricted the agents' behaviour is;
- stability, predictability of the consequences of actions;
- trustfulness, which represents trust between members of the society.

A closed society provides more stability and trust while providing little flexibility and openness [Davidsson, 2001]. Essentially in a closed society, like a company, the members do not change frequently (in the case of a company it only changes when a new person is hired or fired), every members goes to the same destination at similar times, which makes it easier to find carpooling groups and they are more trusting in one another since they have a lot of interactions due to their proximity ([Davidsson, 2001], [Hussain et al., 2020]).

There are a few works focused on MaaS in Closed Societies. Authors Hussain et al., [Hussain et al., 2020] present a matching framework for carpooling for the employees of a large company. The authors

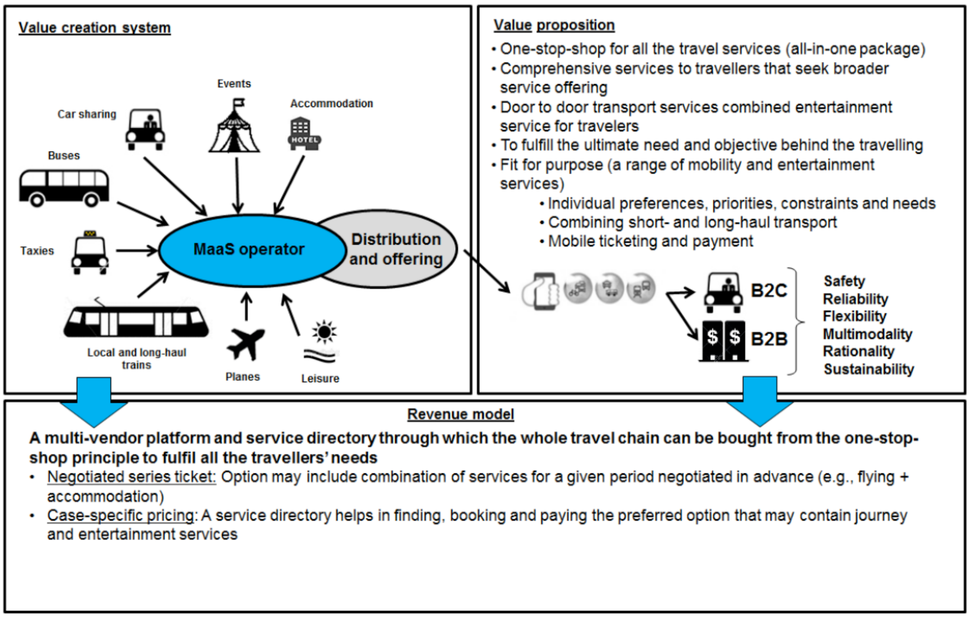


Figure 2.10: MaaS services on a National and International level. Adapted from [König et al., 2016]

state that carpooling would work better in a closed society since there is more trust between the user's and they work in the same location. They touch on some of the incentive factors that would encourage the user's to choose carpooling as their commuting transportation mode such as the decreased cost and relieving congestion. They use monetary cost, excess of time taken to reach the destination, in comparison with a solo trip, time of day preference and degree of flexibility to match the employees.

Another interesting work is one from Hesselgren et al.,[Hesselgren et al., 2019] where they studied how workers accepted and used MaaS solutions after they were implemented in their workplace. They studied the design, development and implementation of Corporate Mobility as a Service (CMaaS) at a large workplace outside Stockholm, Sweden.

CMaaS refers to MaaS services controlled by a corporation, focusing on the transportation to and from the campus but also within it [Hesselgren et al., 2019]. However the changes from integrating these solutions were limited and several barriers were identified to why this may have happened. The integration between these internal mobility solutions and the external transportation services needed a lot of improvement. Corporate policy and culture also appeared to conflict with these services, which limited the results [Hesselgren et al., 2019]. To have a better result and more adherence to MaaS Solutions a better understanding of the users lifestyle, work-life balance and transport practices is needed.

Simply integrating MaaS in the current transport system, without thinking about who is actually going to use them, will not wield good results.

2.2 Artificial Societies

An artificial society, in regards to a Multi Agent System, consists of a collection of agents interacting with each other for some purpose, possibly in accordance with common norms and rules [Davidsson, 2001]. They are a useful metaphor to simulate real societies, the intricacies and interactions between the agents and, in the domain of this dissertation, they are used to study mobility choices.

Agents in a society have different ,sometimes concurrent, goals. The societal construct provides a shared environment through which they can communicate and interact with each other [HORLING and LESSER, 2004].

The Sugarscape Model [Epstein and Axtell, 1996] is one of the most known models to grow artificial societies.

Epstein et al. created this model to generate artificial societies based on three components: agents, environment and rules.

The environment is a medium with which the agents interact and on which they can operate [Epstein and Axtell, 1996].

The rules can dictate the interactions between agent and environment, environment and environment and also between agent and agent. An example of a rule between agent and environment can be "Look around as far as you can, find the site richest in food, go there and eat the food", this rule stipulates how the agent moves according to what he observes in the environment.

Agents have a variety of internal characteristics and behavioural rules. The resulting society from this model is a highly suggestive, although rudimentary and abstract, society [Macal and North, 2010].

Despite the simplicity of agents and societal rules, we are still able to observe interesting emerging phenomena, caused by the interactions between the agents, such as the distribution of wealth between the agents and migration [Epstein and Axtell, 1996].

While the agents first start by not having any relations with each other, they start to connect though the concept of neighbors, establishing a network of friends and forming tribes or communities.

The authors Lacroix and Mathieu,[Lacroix and Mathieu, 2012] propose a model to automatically create agents populations based on demographic data.

The model uses unsupervised learning techniques to infer norms and characteristics that determine the personality of an agent. The model was then applied to create a population of vehicles, used in traffic simulation.

This model, titled behavioural Differentiation Model, is illustrated in Figure 2.11.

Model Agents, as illustrated on Figure 2.11, are middlemen between the model and the simulation. A norm is instantiated on the model agent, the values of the model agent are sent to the corresponding simulation agent and used to control the conformity of the simulation agents values during runtime.

The behaviour of the simulation agents, which characterize their personality, are described using a social norm metaphor. A social norm represents the behavioural patterns that specify

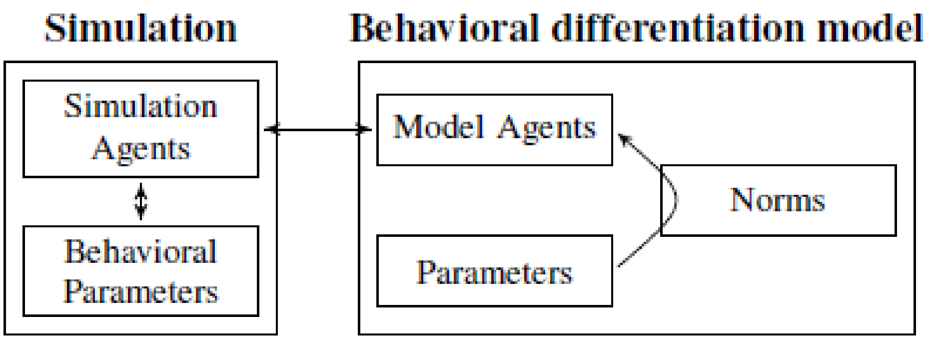


Figure 2.11: behavioural Differentiation Model. Adapted from [Lacroix and Mathieu, 2012]

agents behaviour, allowing the generation of parameter values for agents when they are created and used to control their conformity at runtime.

There are some simulation works in the transportation and mobility fields, which are rather related to the scope of this dissertation, such as the work by Miao et al. [Miao et al., 2011]. In this work, artificial populations are emphasized as being one of the most important components [Miao et al., 2011], since it allows the verification of the effect of changing some parameters that affect the agent system, without it having to be implemented in a real society. The goal of the work was to develop a game-engine-based modeling and computing platform for artificial transportation systems. Earlier practical examples of employing the agent metaphor to represent mobility demand are reported elsewhere [Rossetti et al., 2002a, Rossetti et al., 2002b].

Simulation is also used in other fields. In the work from Zhang et al., [Zhang et al., 2011] the authors used census data and analyzed the structure of a community in China, constructed an artificial society and proposed a method of generating dynamic contact networks. They used their model to formulate intervention measures.

2.3 Social Practices

Social practices are society's accepted ways of doing things in a certain context contextually and materially mediated, that are shared between actors and routinized over time

A practice is a routinized type of behaviour consisting of several connected elements such as activities, things and how they are used, background knowledge in the form of understanding and know-how [Reckwitz, 2002]. A practice can be seen as a pattern which is filled in by a number of atomic actions which are then reproduced by an individual.

Practices are comprised of three elements: materials, competences and meanings [Shove et al., 2012]. Materials include things, technologies and tangible physical objects. Competences encompass the know-how, techniques and skills. Meanings include ideas, aspirations and symbolic meanings.

Regarding what makes a practice a social practice, interpretations differ between authors.

Shove et al.,[Shove et al., 2012] and Reckwitz [Reckwitz, 2002] interpret social as it being a shared, jointly created and maintained, social concept. They interpret social as in the social practice is similar for multiple people but there does not need to be interactions when enacting it.

Another interpretation is presented in the work from Dignum and Dignum, [Dignum and Dignum, 2015] where they deem sociality in social practices as interaction. This explanation is closed to the definition of a social activity, an activity that can only be done in the presence of other people, such as greeting or discussing.

Example of a social practice is illustrated on Figure 2.12

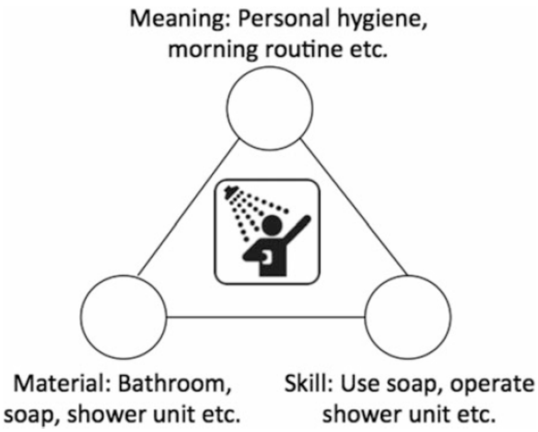


Figure 2.12: Social practice of showering and the underlying elements. Adapted from [Narasimhan et al., 2017]

According to the authors Narasimhan et al., [Narasimhan et al., 2017], practices rarely occur in isolation, they mostly come as bundles to make up lifestyles or habits. The example illustrated on Figure 2.13 combines various individual practices such as drying and storing the clothes into a bundle, since they are often performed together, making up the laundry bundle.

An important aspect to mention is that social practices function more as a behaviour guideline than an obligation. They indicate expectations of the behaviour of the actors involved in the practice, but they do not guarantee that the actor will act exactly as expected [Dignum, 2018].

Dignum's work [Dignum, 2018] proposes a formalization of a social framework for agents based in the concept of social practices to represent the interactions between agents, arguing that social practices facilitate the practical reasoning of agents.

Concepts the authors use to define social practices are context, meaning, expectations and activities. Context includes actors, resources used by the actions in the practice, places etc Meaning represents the social interpretation of the actions. Expectations include possible activities expected within the practice, the rules of the behaviour within the practice, the trigger condition for the social practice to start and the end condition, which indicates how the social practice ends. Activities are the possible actions used by the actors in the practice and the requirements the agent is expected to have in order to perform the actions.

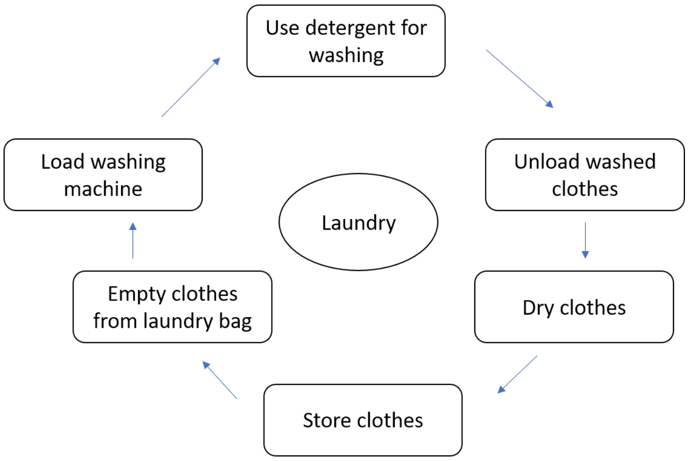


Figure 2.13: Practices that make up the laundry bundle. Adapted from [Narasimhan et al., 2017]

Another interesting work to mention is the one from authors Mercuur et al., [Mercuur et al., 2018]. This work provides the model of a Social Practice Agent, which is used to enable the use of Social Practice Theory in agent-based simulations.

2.4 Incentive Policies

A policy represents a plan of action, agreed or chosen by someone, that will impact present and future decisions [pol, 2020]. An incentive encourages someone to do something [inc, 2020].

Incentive policies are policies designed with the purpose of encouraging some desired changes. In this work, when talking about incentive policies, we will be referring to policies used to change the commuting habits of individuals to more sustainable choices (e.g. shifting from singular vehicles to shared ones).

Incentive policies can be positive for an individual, as for example a policy that rewards a person with two euros for using a public transport mode, or negative, like a punishment, when for example the policy charges the person with two euros toll.

Positive incentive policies act as an encouragement, our example would encourage people to use public transportation, since they would have a monetary gain.

Negative incentive policies act as a deterrent to use certain transport modes, and consequently encourage the use of others. In our example, with the added cost, using private transport would be less enticing than before.

Both positive and negative policies can have the same goal, which in the examples provided and in this dissertation, is to discourage people from using private transportation modes and encourage people to use mobility as a service transport modes.

In the work from Hussain et al.,[Hussain et al., 2020] the authors discuss different incentive factors which are important for carpool to be a feasible option in a large company. They use monetary cost, excess of time taken to reach the destination, in comparison with a solo trip, time of day preference and degree of flexibility to calculate the users utility. Their work focuses on carpooling in the context of a company since its easier to agree to carpool inside a company since the users are more likely to trust each other.

The work of Gomes [Gomes, 2019] explores mobility as a service and concepts related to it. It simulates a society and their adoption of some MaaS services such as Metro and Bus while also seeing how monetary incentives could influence the adoption of MaaS services versus the users' private transport. Although this work lacked experimentation with different incentive policies, the results of using incentive policies could still be observed.

In the work from Kokkinogenis et al., [Kokkinogenis et al., 2014] the authors propose a methodological framework for policy evaluating in multimodal scenarios which is used to explore how market based and incentive based policies can affect the choice of mean of transportation between private and public transport in a multi agent system simulation.

In [Baghcheband et al., 2019] authors consider a minority games setting to assess policy-making scenarios in a bi-modal transport network.

Schedule flexibility, cost, safety and time are important factors mentioned in the work of Tischer and Dobson[Tischer and Dobson, 1979] that users take into consideration when choosing or switching from one mean of transport to another.

In the work of author Levin [Levin, 1982] there were 2 experiments conducted with the purpose of investigating how different factors such as the driving arrangements, size of carpool, distance traveled and others influenced the choice between driving alone or carpooling.

The aspects used to rate the situations were comfort, economy, convenience and overall desirability. In the end, the most important factors taken into consideration by the users were comfort and convenience. In situations where a trade-off exists between comfort and economy, for example more people in a carpooling group is better in terms of economy because each person would pay less but worse in terms of comfort and convenience because there are more people in the car and it would take longer to pick everybody up, the users would choose the option with the best comfort.

Using the results from the works of Tischer and Dobson[Tischer and Dobson, 1979] and Levin [Levin, 1982], we can design more effective incentive policies that take those factors in mind.

2.5 Chapter Summary

In this chapter, we presented an overview of the concepts which are more pertinent to this project.

First we gave a definition of mobility as a service, which is presented as a possible solution to the mobility issues we have in urban areas, aiding us to have a more fluid mobility, with less congestion, reduced travel time and overall reduction of emissions of pollutant gases to the environment.

MaaS is still on the early phases and is not the mainstream mobility approach. The way to integrate it into the current transport sector is still up to discussion.

While currently there are some MaaS projects, with a focus on large open communities, we propose starting in a smaller more contained community with particular characteristics such as the trusting bonds between the members. A lot of closed communities adopting MaaS solutions can have an impact on the environment rivaling the one of a single open community.

To implement this work we propose social simulation of closed communities, through artificial societies.

Artificial societies are a very useful metaphor since they allow for experimenting different things without having the consequences and costs of implementation in a real life society and can still bring interesting results which could eventually translate to the real world.

To build the society we have the concept of social practices, which present the possible ways someone could act in a situation depending on the context.These social practices should be faithful to the society being modeled.

Incentive policies represent the possible changes regulators or stakeholders could make in order to change the perceived utility for different mobility modes for the agents in the community, in order to influence them.

Table 2.3 illustrate gaps found in the literature review.

Table 2.3: Gap analysis from related work

	Transport	Artificial Society	Real Data	Closed Community	Social Practice	Incentive Policy
[Hussain et al., 2020]	x		x	x		
[Hesselgren et al., 2019]	x		x	x		
[Epstein and Axtell, 1996]		x				
[Lacroix and Mathieu, 2012]	x	x	x		x	
[Zhang et al., 2011]		x	x			
[Dignum, 2018]					x	
[Kokkinogenis et al., 2014]	x	x				x
[Gomes, 2019]	x	x			x	x
Our approach	x	x	x	x	x	x

Chapter 3

Methodological Approach

The purpose of this chapter is to present in more detail the proposed approach, which consists of a social simulation model to assist in the analysis and implementation of incentive policies resorting to a simulator and an artificial society.

Details about the simulation such as the simulation environment and the learning algorithms implemented are also detailed in this chapter.

3.1 General Approach

First off, since our work is focused on closed communities, we need to design a meta-model to characterize them. We need to think about the stakeholders that exist in that community such as the End-Users, Regulators and Policy Makers, MaaS Operators and the Transport Operators.

In order to have a better overview of all the involved parties we created a class diagram. This diagram aids the visualization of the stakeholders and the interactions between them in closed communities. The class diagram is illustrated in Figure 3.1.

Secondly we need to get the answers we received from a survey and use those answers to characterize our population. More details on the data and survey in Section 4.1.1. To have an accurate representation of the users, we need data to characterize them. In order to have that data we accessed a survey, (designed by us which as re-purposed), which was sent to FEUP's students in spring 2019, with questions to help characterize the population mainly in terms of ride sharing. The survey had questions about how the students got to the faculty, which transport modes are used to get to the faculty, their willingness to practice ride sharing with different levels of acquaintance, money spent commuting and others. Full survey is presented in appendix A.

The data has to be analyzed through methods such as factor analysis and clustering so we can extract useful information. A more detailed description about the data analysis part of the work is presented in Chapter 4 section 4.1.1.

Using the class diagram and the collected data our next step is to create an artificial society. This artificial society is one of the inputs in our simulation environment.

Our simulation model is set up on the mesoscopic traffic simulator HERMES [Cruz et al., 2019], which underlies the MAS-Ter Lab framework for smart mobility analysis [Rossetti et al., 2007] based on the concept of Artificial Transportation Systems [Rossetti and Liu, 2014]. It receives the artificial population, social coordination policies and different incentive policies as an input and is capable of simulating the choices the agents of the population make regarding transport mode for commuting. More details in section 3.6. The simulation outputs charts and information relevant for us to assess the performance of the run. Assessment measures are described in section 3.6.2.

3.2 Model

The aim of our project is to develop a meta-model that characterizes closed communities, which can then be used as a reference model to provide a better understanding of that type of communities.

We adapted the work of Gomes [Gomes, 2019], which proposed a meta-model that described the structure and dynamics of the MaaS concept in a multi-agent system, to the specific needs of our work. While his work was designed with open service market environments in mind, ours focused on closed communities and the opportunities and characteristics they present.

We created a class diagram to better illustrate the more predominant roles that take part in the MaaS ecosystem and the relations that exist between them. The class diagram is illustrated on Figure 3.1.

With the diagram we can have a better idea about the participants in this MaaS ecosystem and transport market and which roles they take on. Table 3.1 explains in more detail the stakeholders' roles in the model.

The class "Service" in our work is specific to mobility related services so we are talking about services like:

- Transportation Services (e.g. bus, train, metro etc)
- Transit on-demand (e.g. taxis, Uber, etc)
- Rental
- Parking
- Fuelling/Charging
- Ride Sharing

The stakeholder Authority can be seen as an authority that rules over the transportation market in general but, in this case, it's seen in the specific instance of the community, so we are talking about the Community Administrators. Community Administrators are the people responsible for what happens in the organization and, in this situation, more specifically about the transportation

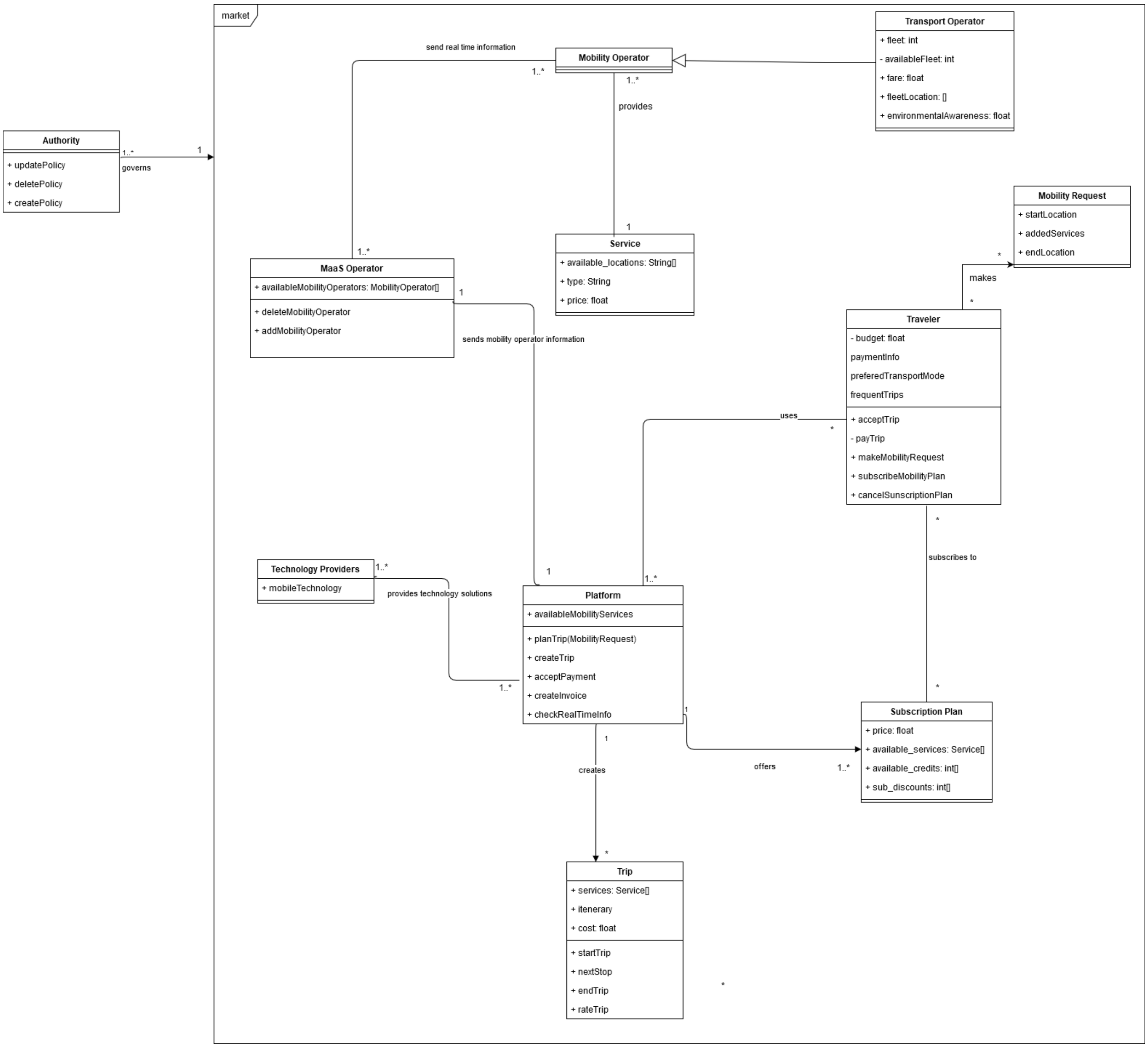


Figure 3.1: Class Diagram.

services, carbon footprint and the travelling habits of the organization members. They monitor the performance of the community in terms of MaaS. They have certain goals and can create policies/incentive polices to help spread the use of MaaS solutions in the community. Similar to a more Authority role since it takes on a more administrative /commanding role but for the specific closed community instead of the general population.

We will now explain, in Table 3.2, with more detail what goals the stakeholders have and the interactions that exist between the participants in this closed community mobility market.

There are a number of interactions between the participants illustrated on 3.1.

- **Travelers:** They have to interact with the MaaS Operator since they are the ones that provide the travelers with mobility packages or single trips that satisfy their travel needs and they

Stakeholder	Role
Authority	Enabler of MaaS. Responsible for transport policy and strategies. They should provide policy frameworks and recommendations for the sustainable development of the market, financing, passenger rights, privacy, security and safety. They monitor the performance of the market, keeping the passenger's interests in mind. Responsible for transportation and traffic planning. Manages the public transport in the region, provides locations of stops and stations.
MaaS Operator	Responsible for combining existing mobility services and present them to the Users/Travelers in a single platform capable of providing personalized transport plans tailored to the user's needs. Responsible for providing a smooth and enjoyable experience to the User.
Mobility Operator	Suppliers to the MaaS Operator. They have the transport services and make them available for the MaaS Operator. They provide fares, vehicle information, booking information, availability and locations to the MaaS Operator.
Traveler	These are the end-users of the MaaS platform. MaaS is designed to make transport more flexible, easier and more sustainable to the Travelers.
Technology Provider	They provide key enabling technology and services to the MaaS Operator. Some services they provide include mobile ticketing and payment.

Table 3.1: Stakeholders in the MaaS ecosystem. Adapted from [Kamargianni and Matyas, 2017] and [König et al., 2016]

also interact with other users since they can have a trusting relationship with each other.

- **MaaS Operator:** Responsible for combining multiple transport related services into a platform, so it will interact with Mobility Operators, in order to have their services available for the travelers. He also interacts with the Community Administrator, since the administrator and the MaaS Operator may need to have a contract so the MaaS Operator can operate in the community.

- **Mobility Operator:** Responsible for providing the service used by the Traveler. Sends and receives information from the MaaS Operator regarding his service.

- **Community Administrator:** Responsible for monitoring everything that happens in the community related to mobility. He can interact with every participant in various degrees since his decisions impact the whole system.

Agent	Main Goal	Soft Goal
Community Administrator	Regulate and improve the transport systems related to/within the community.	• Minimize impact to the environment • Decrease carbon footprint • Decrease organization costs
MaaS Operator	Generate trip for the traveler.	Satisfy the Traveler needs.
Mobility Operator	Transport Traveler to the destination.	Take traveler to destination as fast as possible.
Traveler	Reach the destination.	• Arrive at the destination as soon as possible • Get best value for money • Have a somewhat comfortable trip • Minimize impact to the environment

Table 3.2: Agents and their Goals. Adapted from [Gomes, 2019]

3.3 Artificial Society

In the context of Multi Agent Systems, an artificial society consists of a group of agents that interact with each other with some purpose in mind and possibly in accordance to some general rules or norms which every agent abides by. Agent societies are a useful metaphor to simulate real societies and they are used in this work to study the mobility choices of the members of a closed community.

The members of the society are represented by agents. Members have multiple characteristics that help define and differentiate them from one another. The sources of their characteristics are the survey we mentioned before and other sources such as articles. A more detailed explanation is in 4.2. After this process the agents now have values for their characteristics.

The next step is to form friendship relationships between the users. That process is explained in more detail in section 3.4. Now that every agent has values for their characteristics and relations are formed between them the agent society is completely formed.

In our work the only decision the users have to take is related to which, of the available modes of transport, will they chose to commute to a destination. Common ways of travelling are Private Transport, like a car or a motorcycle, Public Transport, like a bus or train and Ride Sharing, which involves sharing your trip with another person/people but in a car for example, instead of a bus.

We designed an Utility function based on the work from Kokkinogenis et al., [Kokkinogenis et al., 2014]. to quantify how good a certain way of travelling is according to certain parameters. More details about this function in section 5.5

In order for the agents to experiment with various travelling methods and figure out the one which is the best, the most useful, for them, the learning algorithm used is Reinforcement Learning. Reinforcement Learning is an area of machine learning where the agent learns by trial and error, interacting with the environment and using the feedback he receives from the environment to eventually learn what action or actions to take in order to maximize his reward. In our work the agent only needs to learn which transportation service to use in order to maximize the value of the utility function mentioned above, but we could have a more complex environment that required more interactions and more actions.

3.4 Relation Formation

In our work, such as in real life, users can form relations with each other, which can be positive or negative in nature, however we are focused on positive cooperative relations which we called friendships.

Each user has a certain number of friends that is drawn from a normal distribution. The number of friends follows a normal distribution with mean 3 and standard deviation of 1. After knowing the number of friends for each user, instead of randomly pairing them off we decided to add a bit more realism to that process and separated potential friends into categories.

These categories group users into:

1. Users from same course and year - 50%
2. Users from same course but different year (either the year above or bellow) - 20%
3. Users from different courses but same year - 20%
4. Users from different courses and years - 10%

We added probabilities to each of these categories. What they mean is that, regarding closed friends, there is a 50% probability of the friend being from the same course and year while only a 10% of the friend being from a different course and different year. This happens because there are more interactions between people from the same course and year, so there is a higher probability of finding friends within that group.

3.5 Reinforcement Learning

Reinforcement learning is an area of machine learning that concerns itself with how software agents can learn something, receiving only numerical rewards to guide the learning process. Reinforcement learning problems involve learning how to map situations and actions in order to maximize a numerical reward signal. The agent learner is not told which actions to take and instead must explore the surrounding environment, trying out actions, in order to discover which actions yield the most reward [Sutton and Barto, 2018]. Since the actions tried out by the learner agent end up influencing later inputs we are dealing essentially with a closed-loop problem. In more complex systems the actions may affect not only the direct immediate reward but also subsequent actions and rewards. In our work that does not happen because it's a one time choice and not chained choices [Sutton and Barto, 2018].

A good example to better understand reinforcement learning is a mobile trash collecting robot that must decide if it enters the room in order to search and collect more garbage or if it should start to find it's way back to the charging station. That decision, action, is based on the current charge level of its battery and how quickly and easily it has been able to find the charging station in the past ([Sutton and Barto, 2018]). There is no definitive rule of when he should charge and he does not know, in the beginning, when he should get back to the charging station. It's only through exploring his environment and receiving feedback from his actions (through the reward signal) that he will learn what the best sequence of actions is.

The agent while training has two behaviours:

- Exploration - agent chooses actions which are unknown or have a lower expected reward
- Exploitation - agent chooses the action at each state which currently has a higher expected reward.

The agent could potentially behave in a greedy way and select only the action that has the highest expected reward but that way he would not find actions that could potentially be more beneficial.

While training the agent has find some balance between exploration and exploitation since he needs to explore which actions he can take in order to find the actions that bring about the highest rewards and later exploit them. To have this balance between exploration and exploitation we have a probability ε that starts with the value of 1 and decreases over time. This way we have a probability ε of selecting randomly amongst the available actions, all the actions have the same probability of being chosen, independently of the expected reward values.

ε is updated after each action selection using:

$$\varepsilon = \varepsilon * 0.999 \tag{3.1}$$

After training the agent should be taking the actions that lead it to the state with the highest possible reward which, in our case, means that he should choose the transportation service which brings him the highest utility.

3.5.1 Deep Q-learning

In order to talk about Deep Q-learning we must first explain what Q-learning is. Q-learning is a model-free reinforcement learning algorithm that provides agents with the capability of learning how to act in an optimal way in Markovian domains [Watkins and Dayan, 1992]. What we mean is that given any of the possible states in the environment (s) and any of the possible actions (a) the possible reward for that pair state action is illustrated in Equation 3.2.

$$Q(S,A) = r(S,A) + \gamma \max_{a} Q(s',a) \tag{3.2}$$

Equation 3.2 gives us the expected reward value of taking action A in state S. s' represents the next state and γ represents the discount factor. This factor determines how much the possible future rewards influence the reward signal.

Every single one of these state action pairs are stored in a table so that they can be easily accessed later. This table, besides storing the reward value of the pairs, also updates them according to future rewards. The problem appears when the environment has a lot potential states and actions (think about an environment with thousands of states and hundreds of actions). The amount of memory required to save and update the table would be enormous and the amount of time required to explore every single possible state to fill the Q-table would make the process a lot slower. A way to make the learning process faster is to use Q-learning but with a neural network to approximate the Q-values - Deep Q-learning.

Figure 3.2 illustrates in a basic way what differentiates the Q-learning algorithm from the Deep Q-learning algorithm.

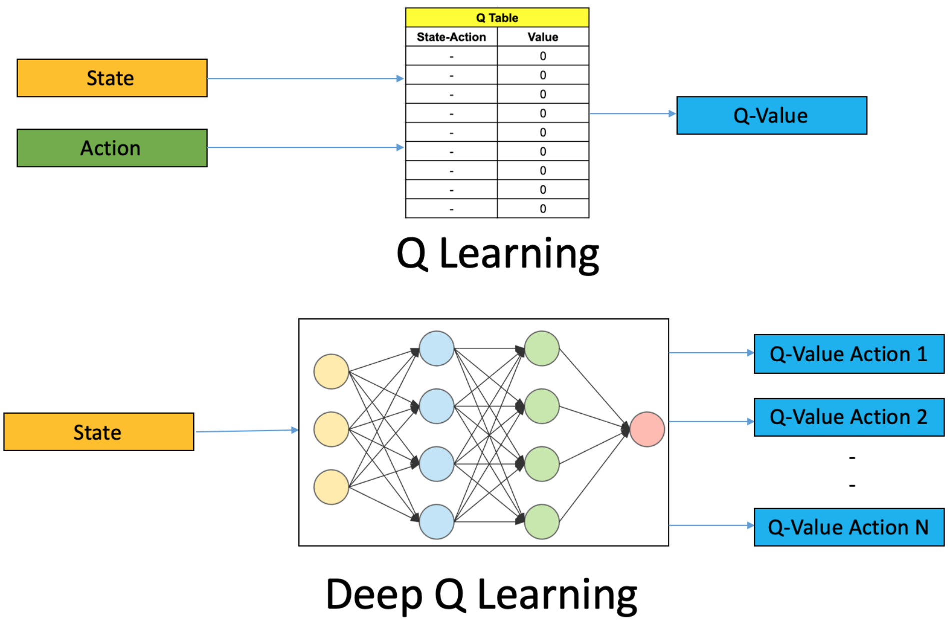


Figure 3.2: Comparison between Q-learning and Deep Q-learning algorithms [Choudhary, 2019]

In Deep Q-learning we use a neural network to approximate the Q-value function (value that represents the expected return of taking an action from a certain state). The neural network, receives as input, information about the user such has the distance he lives from the destination and status about ownership of a private vehicle and also the start time of the commute and returns the Q-Values of all the possible actions (the possible transportation services). The use of a neural network allows for generalization which means that Deep Q-Learning could perform well in states that it never experienced.

Figure 3.3 illustrates the Deep Q-learning algorithm.

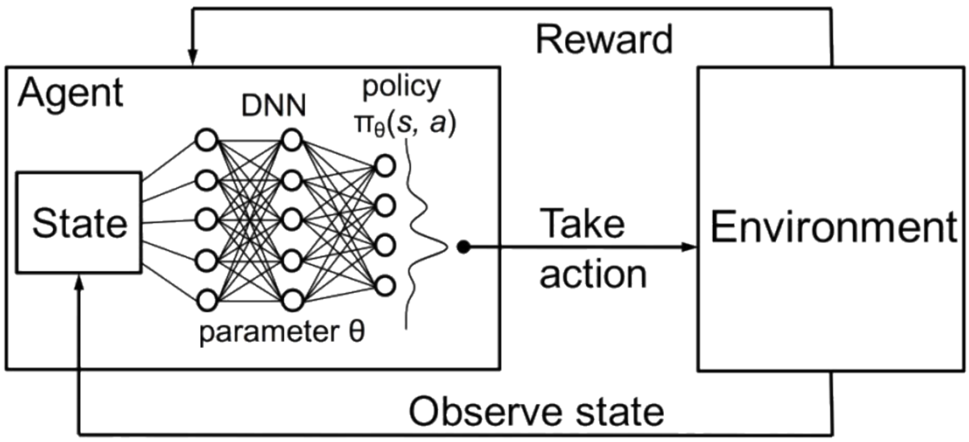


Figure 3.3: Deep Q-learning algorithm [Mao et al., 2016].

The neural network is trained based on the input and the utility received from using the chosen action, calculated using the utility function described in Section 5.5. Figure 3.4 illustrates the neural network used in our work.

When talking about Deep Q-learning and Q-learning we talked about States, Actions and a Reward signal. We will now explain in a more concrete way the value of these different factors in our work.

Actions: The agent can choose from different mobility services to travel from his starting point to the destination. In our work we have implemented 5 different mobility services from which the agent can choose from, so the learner has in total 5 different possible actions.

Actions: The agent can choose from different mobility services to travel from his starting point to the destination. In our work we have implemented 5 different mobility services from which the agent can choose from, so the learner has in total 5 different possible actions.

States: each state has information about the agent, which includes information about desired time to leave for destination, personality, ownership status of private vehicle and bicycle, distance from destination, available seats in private vehicle and boolean variables that represent if the user can walk or bicycle to the destination. All these variables are explained in more detail in Section 4.2.

Rewards: the reward signal received when performing an action depends on the utility function implemented. Details about our utility function can be found in Section 5.5.2.

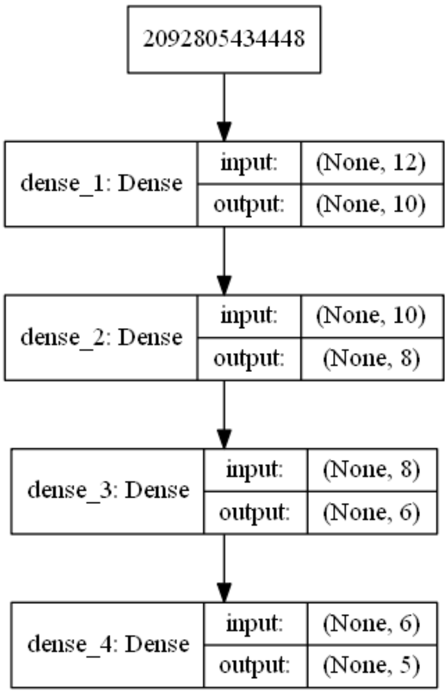


Figure 3.4: Neural network model used for Deep Q-learning

3.5.2 Ensemble Learning

It is important to notice that the utility function is one of, if not the most important element of the learning process, since it states how useful an action is, dictating what is a "good" action and what is a "bad" action.

An approach that can possibly improve the learning process, contributing to faster and better solutions, is to transform a single-objective reinforcement learning problem into a multi-objective problem.

Multi-Objectivization refers to the process of transforming a single-objective problem into a multi-objective problem either by decomposing the original function or by adding extra objectives. These extra objectives are generally based on some expert domain knowledge and are only there to speed the learning process and steer it to the right path.

There are multiple examples of these two approaches in the literature such as in the work of Fieldsend [Fieldsend, 2009] where multi-objective through decomposition lead to the formation of better decision trees in some cases and in the work of Jensen [Jensen, 2005] where the author investigated the job shop scheduling and travelling salesman problems and found that adding additional objectives helped the performance of the algorithm, solving the problems faster.

According to authors Brys et al., [Brys et al., 2017],combining a multi-objective function with the use of ensemble techniques can significantly boost solving performance in reinforcement learning.

Ensemble techniques consist of combining multiple algorithms operating on the same problem and using them to improve the performance of these problems. We can have several learning algorithms such as Q-Learning and SARSA, learning on the same problem, combine them at the action selection stage, to get their scores for each action, and select an action according to their combined scores, which may lead to a better decision than if it were just one algorithm alone.

For combining the scores of the different algorithms we can have different strategies such as majority voting or rank voting [Brys et al., 2014] and for tie breaking we can decide which algorithm's decision is worth more.

We can also apply these ensemble techniques in a new way. Instead of using different learning algorithms we can use the same learning algorithm (e.g. Deep Q-Learning) to learn a different part of the reward signal. According to authors Brys et al,[Brys et al., 2014], the diversity required for ensembles to provide a benefit lies in having different reward signals and not necessarily on different learning algorithms.

This was the way we chose to implement ensemble learning in our work: have the same learning algorithm (Deep Q-learning) but have different learners for different segments of the reward signal.

Our utility function is illustrated on Equation 3.3.

$$U_{Total} = U_{Cost} + U_{Time} + U_{Environmental} + U_{Comfort} \tag{3.3}$$

We can see that the equation is separated into 4 different components - $\mathrm{U_{Cost}}$, $\mathrm{U_{Time}}$, $\mathrm{U_{Environmental}}$ and $\mathrm{U_{Comfort}}$- each learner will only have access to the the reward signal from that component.

In the action selection stage, each learner will vote on one of the available actions. The selected action is the one voted by the majority. In the case of having reached majority, then that action will be selected, in the case of a tie, the action chosen by the learner responsible for $\mathrm{U_{Cost}}$ will be the deciding factor, in the rest of the situations a random action will be selected.

After selecting the action and getting an updated reward signal, all learners will be updated based on the reward segment.

3.5.3 Weighted Average Experiences

Weighted Average Experiences is a different reinforcement learning technique explored in our work. This technique consists of having a learner agent that saves, in different queues, the last experiences he had with each of the possible actions. Similarly to the other techniques we discussed in previous sections such as Q-Learning, it's also important to talk about States, Actions and the Reward signal.

States: states have the necessary information to characterize the surrounding environment and differentiate them from the other states. In our work the agent only has one problem he needs to solve, which is decide which transportation service he should use to commute to either work or school, and then the decision process ends. In Q-learning, states are required to differentiate between multiple users, using their individual characteristics, to select between actions. Since each learner agent only learns and dictates the actions for one individual agent, and we only have one decision to make, there is not a need for states.

Actions: the agent can choose from different mobility services to travel from his starting point to his destination. In our work we have 5 different mobility services at the agent's disposal that he can choose from. The learner agent has a total of 5 different actions.

Rewards: the reward signal given to the learner agent after he performs an action comes from the utility function implemented. Details on the utility function are available on Section 5.5.2.

The learner agent has two different behaviours, Exploration and Exploitation, to explore the environment and the different actions and then exploit the one that has a higher expected reward.

The way the reward signals are saved and how to update the expected reward for an action is similar to how it operates in the Q-learning algorithm. While in Q-learning we use a table to save, for each pair (state,action), the expected reward value, in this algorithm the expected reward for each action is saved in a list. That list is updated by the means of a queue. There are a total of 5 queues, one for each of the possible actions, and what happens is that the queue serves as the agent's memory, saving a number of past experiences where he explored that action and the reward he received. The queue is finite, saving up to 200 memories, and is constantly updated with the newer memories, deleting the older experiences.

After a minimum of 20 experiences for each action, the learner agent can start to update the expected reward list. Until then, the expected reward is 0 for all the actions.

When that minimum is reached the value of expected reward for each action is updated, using a weighted average of the experiences. Since we are saving up to 200 experiences we decided to separate them into different groups with different weights. The first group is the last week, which are the most recent 7 days of experiences. The second group is related to the last month, which are the 30 more recent days. Third group encompasses the last 3 months, 90 days, while the rest of the experiences are in the fourth and final group.

Table 3.3 shows the different weights for the 4 groups. In the case where the agent does not have enough information to be separated into the 4 groups, then we have the different weights illustrated on Tables 3.4 and 3.5 . The most recent experiences are the ones with more weight, more significance, and the weight decreases with the age of the experience.

Table 3.3: Weights for more than 90 days

Total Number Experiences	Weight
Last 7 days	50%
Last month	30%
Last 3 months	15%
Remaining	5%

Table 3.4: Weights for less than 90 days

Total Number Experiences	Weight
Last 7 days	0.5
Last month	0.3
Remaining	0.2

Table 3.5: Weights for less than 30 days

Total Number Experiences	Weight
Last 7 days	0.5
Remaining	0.5

The weighted average is calculated for each of the actions and is then used as the expected reward for that action. The agent will exploit the action that has the highest reward.

3.6 Simulator

To set up and carry out our simulation experiments, we have extended the traffic simulator HERMES [Cruz et al., 2019], which is an event-driven mesoscopic simulation of advanced traveller information systems. Other traffic simulation approaches can also be considered, such as the macroscopic and the microscopic models, although the former is not quite appropriate to represent an artificial society of commuter agents. More about traffic simulation approaches and representational granularity can be bound in [Passos et al., 2011, Timóteo et al., 2010].

We introduced new concepts such as Users, Mobility Operators and Transportation Services which represent the end-users, suppliers of transportation services and the mobility services available to the Users.
Numerous other functionality and changes were made to the base simulator such as:

- Created a JSON file with information about the graph such as information about its edges, number of users and distributions related to the characteristics of the users, in order to maximize flexibility.JSON file used is in Appendix C.

- Added the functionality of saving an existent agent population into a file and import an agent population from a file, in order to be able to make a more accurate comparison between scenarios;

- Implemented Deep Q-Learning, Ensemble Learning, Weighted Experiences Average and other learning techniques;

- Added the necessary changes for the inclusion of different incentive policies;

- Created the concept of an organization and added a parking lot;

- Implemented matching algorithms for different services;

- Save information from each run necessary for the the performance measures

Example of the graph is illustrated in Figure 3.5.

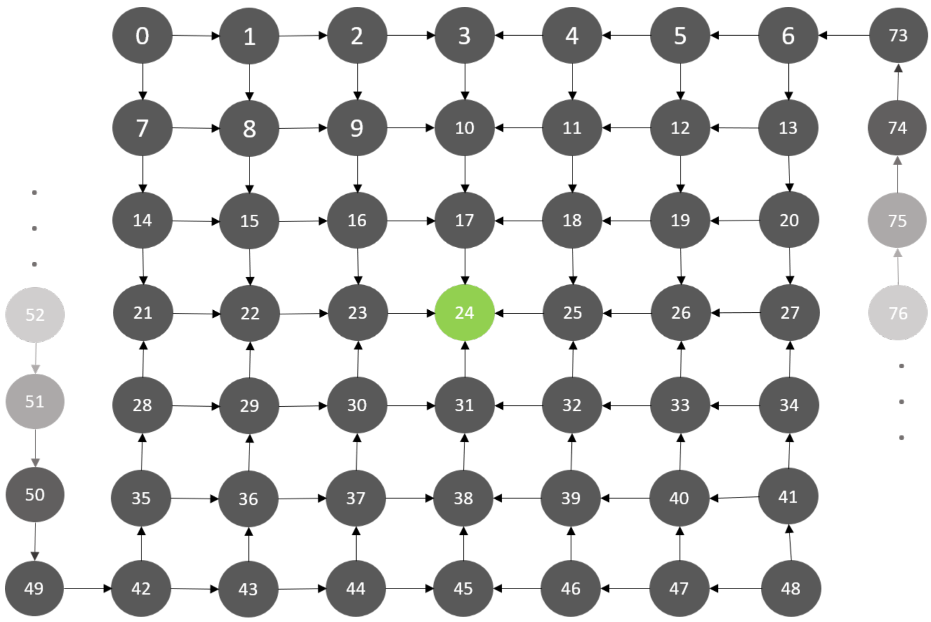


Figure 3.5: Graph

In Figure 3.5 we present a grid-like representation of a city center in which each edge is directed towards the middle node, which is the destination node (e.g work, university,etc.), and each edge can be traversed by 4 possible travelling modes. Eventually more modes could be added and also possibly different services related to transportation. Such services range from vehicle rentals to parking spots and charging stations for electric vehicles.

The nodes represent possible origins (e.g residential locations) for the users and each edge has one kilometer of length. The maximum distance a user can live from the destination is 30km.

The agents, which represent users, have a simple utility function so that they can learn which transportation service to choose from using Reinforcement Learning techniques.

Mobility Operators are responsible for only one transport service.

From the literature review we decided on different values and characteristics to differentiate mobility services, which influence which mobility service the user chooses.

Examples of mobility services are Private Vehicles, which could be electric or not, Ride Sharing and Public Transport.

Figure 3.6 illustrates the process the user goes through after being created.

If, for some reason, either it be schedule incompatibility or not enough space in the service, the user ends up not getting matched to the chosen mobility service, the user receives a negative utility value to show that this service is not compatible for him.

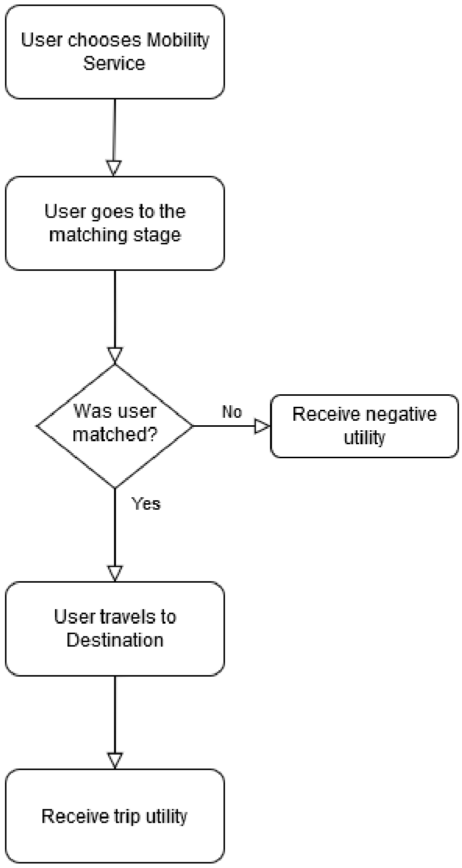


Figure 3.6: User throughout scenario

If the user is matched to the chosen service then we create Actors. Actors represent the individual mobility services, what that means is that each actor represents one specific vehicle, that travels through nodes and edges of the graph until the destination. Each actor can represent multiple agents, since multiple agents can travel in the exact same vehicle (e.g. public transport).

3.6.1 Transportation Service Information

Each transportation service has the following characteristics:

- Cost (in euros) - all costs related to the trip;
- Comfort - how comfortable the service is, from 0 to 1;
- Awareness - how environmentally friendly the service is, from 0 to 1;
- Emissions (g/km) - emissions of greenhouse gases, notably C02;
- Transport Subsidy - help provided by the organization to compensate for the user's trips using this mode of transport;

The Public Transport mode has an added information variable which is the schedule. Using bus as an example, each individual bus will have a predefined route and the time it will approximately pass by in each stop, like buses in the real world.

3.6.2 Performance Measures

Regarding the assessment of our work we have the following metrics, separated into agent's performance measures and organization's performance measures.

The agent's performance measures we would take into consideration are:

- Travel Cost
- Travel Time
- Quality of Service - Time
- Quality of Service - Cost
- Average Total Travel Time by service

Travel Cost represents the total cost of the trip that the user needs to pay for, which includes the cost of going from start to destination and other additional costs such as parking costs.

Travel Time represents the total time spent in the trip. It takes into account both the in-vehicle time and the waiting time.

Our last agent's performance measures are Quality of Service Time and Quality of Service Cost. These two are very similar and compare the time and cost spent in the trip with how much time and cost the trip would be if it were made using a private vehicle. The equation used is similar to the one from the work of Bistaffa et al.,[Bistaffa et al., 2019] but it was adapted to the circumstances of our work. Equation 3.4 illustrates how the Quality of Service - Cost is calculated while Equation 3.5 illustrates the Quality of Service - Time.

The performance measure Average Total Travel Time by service takes into account the in-vehicle travel time and the waiting time for each of the available services.

$$Q\_cost(S) = -\frac{Travel_{cost} - Private_{cost}}{Travel_{cost}} \tag{3.4}$$

$$Q\_time(S) = -\frac{Travel_{time} - Private_{time}}{Travel_{time}} \tag{3.5}$$

S represents the transportation service chosen. $\text{Travel}_{\text{cost}}$ and $\text{Travel}_{\text{time}}$ represent the cost and time of the trip, for the user, while $\text{Private}_{\text{cost}}$ and $\text{Private}_{\text{time}}$ represent the cost and time of the trip if it had been made using a private vehicle.

Note that when calculating the cost of the trip using a private vehicle we do not take into consideration parking fees.

The organization's performance parameters we would take into consideration are:

- Overall Average Travel Time
- Carbon footprint
- Cost

Overall Average Travel Time presents the average travel time it takes for a user to reach the destination, independently of the service. When talking about travel time we are considering only the in-vehicle travel time.

Carbon footprint measures the C02 emissions produced by the members of the organization when commuting to the headquarters.

Cost represents the sum of costs due to the carbon tax and costs related to the transport subsidy.

Carbon tax is a fee imposed on the burning of carbon-based fuels such as oil and coal. This fee is a way to have users pay for the climate damage they are doing when choosing carbon-based options, acting as an incentive to switch to more environmentally friendly alternatives. According to OECD [OECD, 2019] , in 2018 the carbon tax in Portugal for road related emissions was of 180 € per tonne of CO_2.

Transport subsidy is a help provided by the organization to compensate for the user's trips. The value of the subsidy depends on the transportation service.

3.7 Chapter Summary

In this chapter we presented our meta-model that characterizes closed communities and describes MaaS in those communities. We also discussed the artificial agent society and how it is used to simulate demand in our simulation scenarios.

We presented Deep Q-Learning, which is the learning algorithm used in this work, and other learning techniques that were also taken into consideration and experimented with.

We took a more in depth look into our simulation environment and the changes made to transform it for our needs.

Finally our simulation scenarios were described along with the performance measures we are taking into consideration to evaluate our work.

Chapter 4

Survey Data and Analysis

The purpose of this chapter is to present in more detail the data that was used to build our synthetic population.

We start by first presenting our survey and some charts in order to characterise the sample of respondents who answered the questionnaire.

We then describe the necessary steps we took to transform the collected data into useful data for our population and explain the different characteristics the agents of our population have.

4.1 Survey Design Details

We designed a survey which was distributed amongst FEUP's students with questions to help characterise the population mainly in terms of ride sharing customs. The survey had questions about how the students got to the faculty, which transport modes are used to get to the faculty, their willingness to practice ride sharing with different levels of acquaintance, money spent commuting and others.

This survey, with 563 answers, helped us characterize the users. The survey in it's entirety is available in appendix A.

4.1.1 Data Description

In order for us to better understand and characterize the answers from the survey we present some charts such as Age distribution, mode of transport used to commute and private transport ownership.

Figure 4.1 shows the age distribution of the surveyed.

Since the survey was sent to university students this distribution is not surprising, with 83% of the surveyed being younger than 25 years old.

Despite the majority being young adults, 78.5% of the surveyed have a driver's license which means that the percentage of using public or private transport is not unfairly skewed towards public transport due to the inability of driving. Figure 4.2 represents the driver's license ownership.

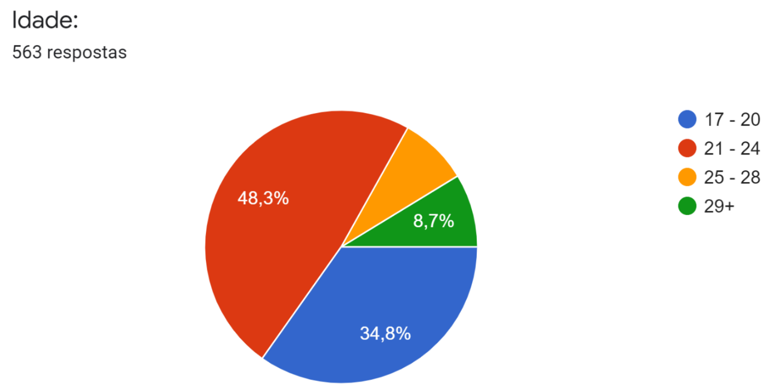


Figure 4.1: Age distribution

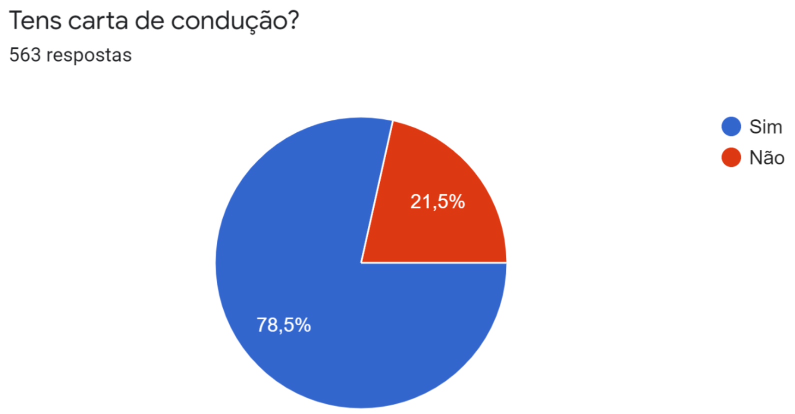


Figure 4.2: Driver's license ownership

Regarding private transport availability for commute the percentages are very similar, with 54.7% not having a private mode of transport while 45.3% have (Figure 4.3).

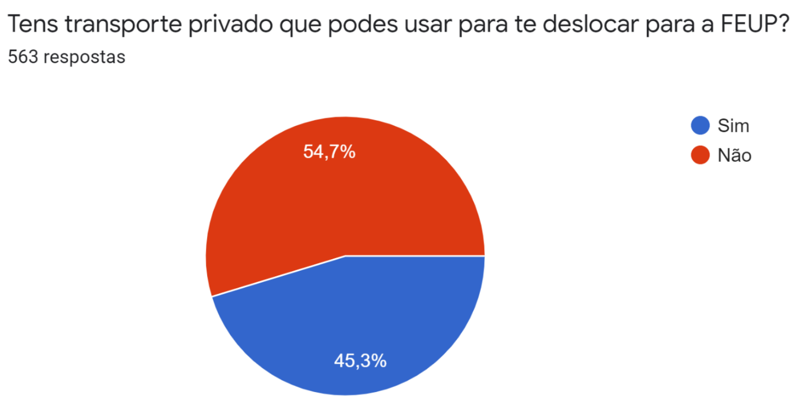


Figure 4.3: Mode of transport available for commuting

This gives us an idea about the possible percentages of users who commute using private vehicle and public transport. Since 45.3% have access to a private vehicle that already gives us an idea about the percentage of users that could eventually use this mode to commute.

One of the most pertinent questions from the survey is the one regarding what modes of transport do the surveyed use to commute. Figure 4.4 shows the distribution between the available services:

- Private Transport - such as car and motorcycle;
- Public Transport - such as bus, train and subway;
- Private and Public Transport - an example would be using private transport from home to the train station and then using the train for the rest of the journey;
- Walking/Riding a bike.

Figure 4.4 shows the distribution of the modes of transport used. 43.2% use public transport, making it the most used way of transport, followed by private transport and walking/riding a bicycle. There are also 8% of surveyed that use both public and private transport, we believe that they use private transport for a small part of the trip such as travelling to the train station and use one or more modes of public transport for the bulk of the trip.

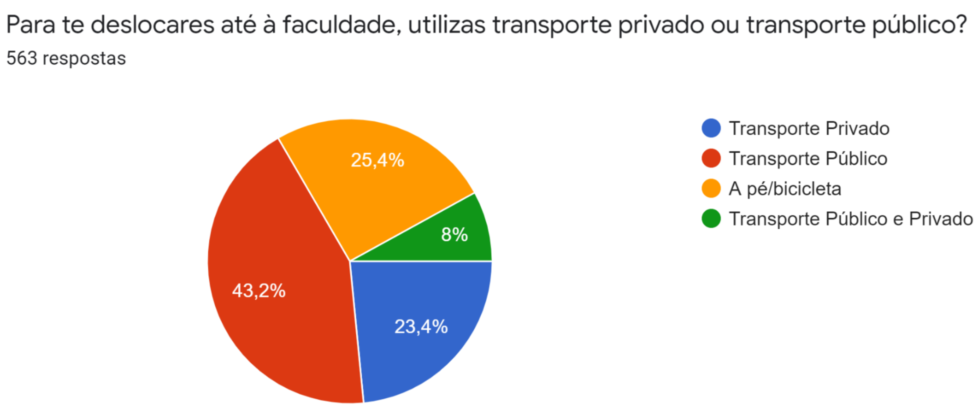


Figure 4.4: Modes of Transport used for commuting

Having an idea about where the members live during the class period is also important. It would be better to have a balanced dataset where we have representation for users that live inside the Porto municipality and also outside the municipality. In the instance of a disproportionate amount of people living either inside or outside, the dataset could then be biased towards one of the transportation service. Figure 4.5 illustrates the distribution of surveyed living inside porto municipality (65.7%) and outside (34.3%).

We now have an idea of the characteristics of the surveyed that will serve as a foundation for our society. As expected the surveyed are mostly young adults with a high percentage that possess

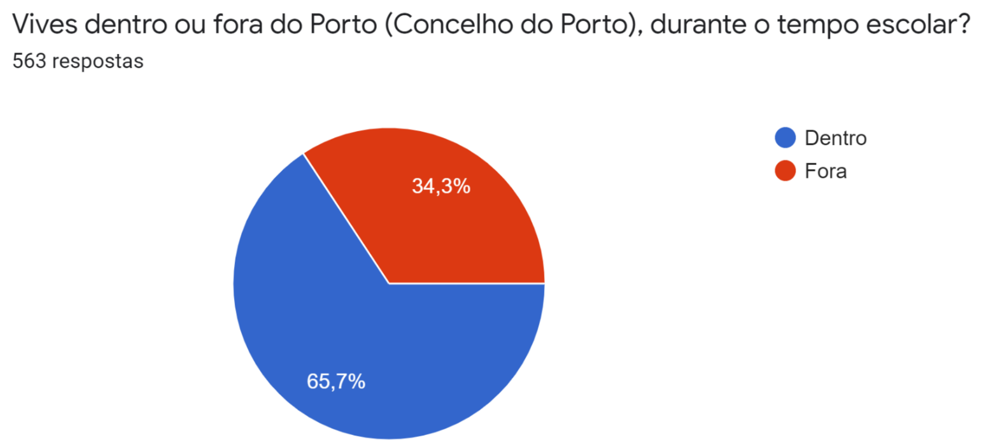


Figure 4.5: Living inside Porto Municipality

a drivers license and a diverse use of transportation services,with public transport being the most used service.

Several reasons why that could happen are the high supply existent around the faculty and also the existence of monthly discounted subscription for students that make it the cheaper alternative.

We also can see a high percentage of people that either walk or bike to school which is something unusual if we think about workplaces but very normal for our case since we are talking about a faculty.

4.1.2 Data Cleaning

Data is not always up to par to the actions that it will be used for. While some basic checks can be input into the form, such as if we want a text answer check if the answer provided is textual, there may be some more difficult checks that need to be done. For that reason we need to look through the database and examine it ourselves.

To clean the data, in order to prepare it for the next steps of factor analysis and clusters, we had to:

- Delete entries with strange data values;
- Separate entries which either did not have a value for money spent in fuel or in public transport. The missing values were filled in using a classification technique.

Since we obtained only 563 answers to our survey, all the answers we have are important in order to better characterize our population. While looking at the data we saw that a total of 45 participants did not know how much money they spent either in public(4) or private transport(41), per month, in their commutes. We decided that, using a classification method to help figure out the money these participants probably spent, would produce good results so as to not discard so many answers. Since these are continuous variables we used regression methods.

We tried a number of methods such as Linear Regression [Quadrianto and Buntine, 2016], Decision Tree [Torgo, 2016], Support Vector Machine [Yu, 2016] and k-Nearest Neighbors (k-NN) [Kramer, 2013], using RapidMiner [Hofmann and Klinkenberg, 2013]. Ultimately we used Decision Tree for the classifier of the money spent on public transport and k-NN for money spent on fuel.

Some entries did not have responses for all the incentives so we also decided to not take those entries into consideration, which made it so that in the end,we have a total of 528 responses after this process.

4.1.3 Data Analysis

We decided to use the data from the survey to help better characterize the population and divide them into clusters, according to the characteristics. The clusters and the distribution of the variables within those clusters would be used to generate a more representative artificial population, which is described in Section 4.2.

The data from Section 4.1.2 has 23 variables, which is a large amount. We decided to use Factor Analysis to decrease the number of variables. A new dataset with those new variables would be created and used to form clusters. We would then have more information about the types of people that belonged to each cluster and variables distribution within the clusters to create a more detailed artificial population.

4.1.4 Factor Analysis

Factor analysis (FA) is an exploratory data analysis method used to search influential underlying factors from a set of observed variables, effectively transforming a large number of variables into fewer number of factors [Alhija, 2010].

It's a method used in a lot of fields such as market research, finance and operation research. As described in Section 4.1.3 we will use this method to reduce the number of variables in our dataset, creating a simpler understanding of the relations between variables and subsequently the formed clusters.

Some terms that are useful to keep in mind are:

- Factor: a latent variable that associates multiple observed values of our dataset;
- Eigenvalue: how much of the variance existent in a set of observed variables is explained by a common factor; [Alhija, 2010]
- Factor Loadings: the existent relationship between each observable variable with the underlying factor is called a factor loading. [Alhija, 2010]

The first step in factor analysis is to perform two tests that determine if we can perform factor analysis in our dataset. Without getting into too much detail, the two tests - Bartlett's Test and Kaiser-Meyer-Olkin Test- evaluate if it's possible to find factors in our dataset. We passed the two tests which means factor analysis could be used in our dataset, and so the second step is to chose the number of factors.

Numerous procedures exist to help with determining the number of factors. The most commonly used methods, and the ones we use, are Cattell's scree plot and Kaiser's eigenvalue greater than one criterion [Alhija, 2010]. The scree plot is a line plot of the eigenvalues of the factors. It displays the eigenvalues in a downward curve from largest to smallest. The number of factors chosen is the "elbow" of the plot, which is where the line of eigenvalues seem to level off [Cattell and Vogelmann, 1977].

Figure 4.6 represents the line plot between the eigenvalues and the number of factors. From this figure we decided that either 5 or 6 factors would be the best number.

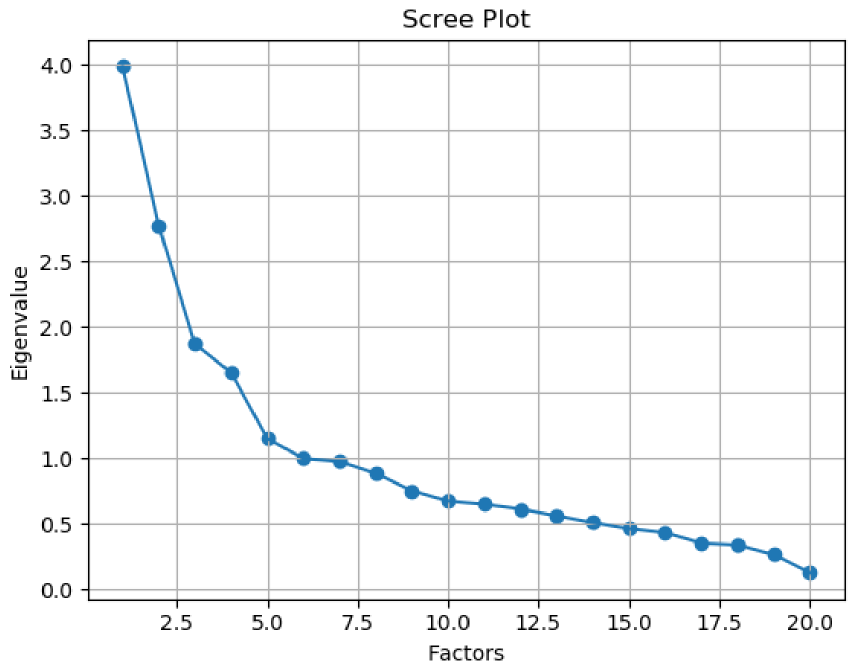


Figure 4.6: Scree Plot

The second method used to decide the number of factors was the Kaiser eigenvalue criterion. Only the factors which have an eigenvalue greater than 1 are chosen. Table 4.1 shows the number of factors and the respective eigenvalue.

Taking both the Cattell's scree plot and Kaiser's eigenvalue criteria in consideration we decided on 5 factors.

Next step is performing factor analysis. Analyzing the factors and the factor loadings for each variable of the initial dataset we have the following factors:

- Friendliness: users with a high value in this factor are more willing to travel with other people;

Table 4.1: Kaiser Eigenvalue Criterion Results

Factors	Eigenvalue
1	3.984
2	2.771
3	1.869
4	1.652
5	1.148
6	0.997
7	0.974

- Susceptible: users with a high value are more accepting of incentive policies and more prone to take advantage of them;
- Transport: This factor relates the use of private transport with money spent on fuel and on public transportation. Users with a high value use private transport to commute;
- Urban: This factor relates travel distance with living distance from the destination and money spent on public transport;
- Willing: Users with a high value in this factor generally ride share their commuting trips;

More details about the factors loadings for each of the factors are available on Appendix B.

Now we have a new dataset where the variables are the five factors described above and can now move to the next stage, clustering.

4.1.5 Clusters

In this work we are going to separate our dataset into clusters which will then be used to characterize the kind of users form our artificial population. To decide how many clusters we should have in our population we used the Silhouette method [Rousseeuw, 1987] in conjunction with the K-Means clustering algorithm [Hartigan, 1975].

First step is to calculate the silhouette score for a range of clusters to find out which one has the highest score. The score helps to determine if the objects are well matched to their cluster and not overlapping. This score ranges from -1 to +1 with a high value indicating that the object is well suited for the cluster.

Figure 4.7 represents the silhouette scores for a range of clusters. The highest value which ended up being chosen was five, so we divided our dataset into five clusters.

Silhouette analysis is used to examine the separation distance between the resulting clusters. Figure 4.8 represents the silhouette analysis for five clusters. We can see that most of the clusters' (clusters 1,2,3 and 4) range includes also negative values, which means that the sample we have may be assigned to the wrong cluster but we do not think they were significant enough to present a problem in our work.

In our new clustered dataset we have the following distributions:

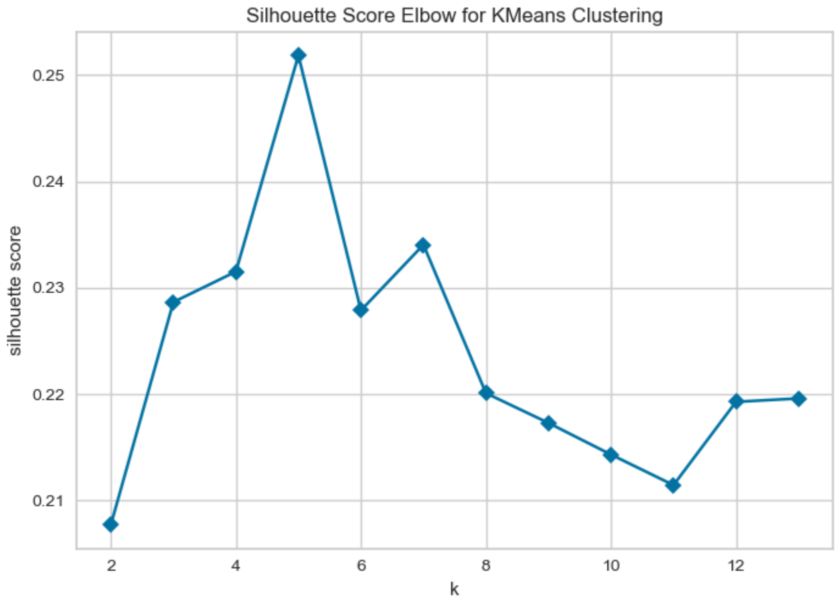


Figure 4.7: Silhouette Score Plot

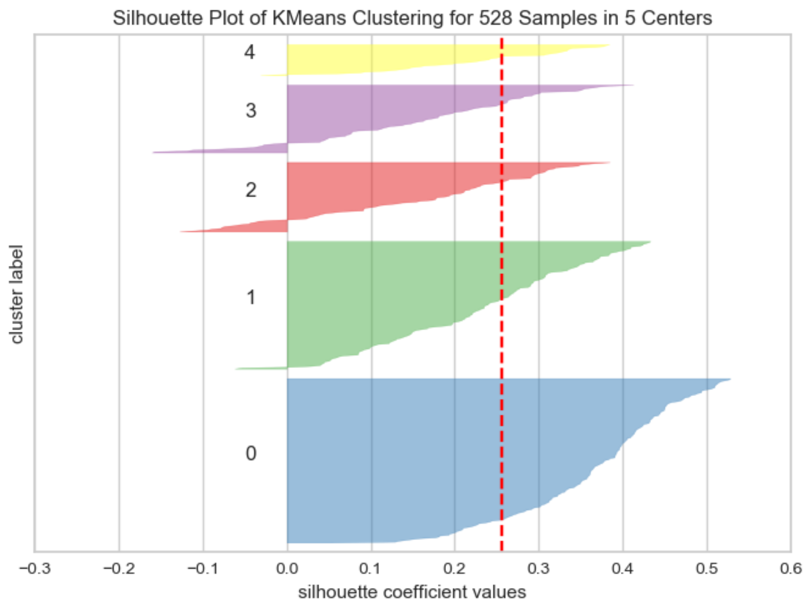


Figure 4.8: Silhouette Plot for five clusters

- Cluster 0 - 26.70 %
- Cluster 1 - 15.91%

- Cluster 2 - 6.81%
- Cluster 3 - 34.85%
- Cluster 4 - 15.72 %

Analysing the relation between clusters and the factors we are able to better characterize the kind of users belonging to each cluster. Figure 4.9 shows the values of mean and standard deviation in each cluster for each factor.

	Cluster 0		Cluster 1		Cluster 2		Cluster 3		Cluster 4	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Friendliness	0.257	0.685	-1.475	0.635	0.132	0.935	0.355	0.646	0.212	0.866
Susceptible	-0.135	0.827	-0.48	0.975	-0.127	1.018	0.253	0.713	0.21	0.762
Transport	1.004	0.44	-0.167	0.756	-0.163	0.795	-0.668	0.266	0.015	0.992
Urban	-0.294	0.515	-0.203	0.603	-0.145	0.806	-0.448	0.352	1.761	0.661
Willing	-0.131	0.281	-0.205	0.32	2.322	0.249	-0.236	0.284	-0.054	0.442

Figure 4.9: Clusters' Mean and Standard Deviation for each Factor

From observation of Figure 4.9 we have a better idea about the types of users belonging to each cluster.

- Cluster 0 has a high value for the Transport factor. People from this cluster use more private transportation which leads to them spending more money on fuel and less on public transport.
- Cluster 1 has high negative value for Friendliness which means that people from this cluster are not keen on trying ride sharing independently of who they ride share with (with the exception of their friends)
- Cluster 2 has a high positive value for Willing. People from this cluster are very open to the idea of trying ride sharing in general, especially with people they have some level of trust with.
- Cluster 3 has relatively high negative values for Transport and Urban. Almost no one has private transport, the most used mode of transport is public transport or bike/walking since they live close to the destination.
- Cluster 4 has a high positive value for urban. Most of the users belonging to this cluster live outside the city, far away from their destination, which means they spent more money in public transports, in comparison with the other clusters.

These clusters are then used to better characterize the users and form a more realistic community, which we will synthesize. Characteristics of the Users such as at what distance do they live from their destination, ownership of a private vehicle and available seats, as well as the values for each factor produced from the factor analysis, all stem from which cluster the user belongs to.

4.2 Artificial Society - Users

Agents in our society have multiple characteristics, some which are derived from the cluster they belong to and some which are more general. In this section we are going to discuss the cluster specific variables.

The agents have the following characteristics:

- Cluster - one of possible five
- Distance - distance from the user's house to the destination, in kilometers
- Personality - characteristics that represent a more human side of the user
- Has Private Vehicle - indicates if the user owns a private vehicle or not
- Available Seats - how much free seats the user has in his vehicle

Regarding what we titled "Personality", it has multiple factors used to characterize the users which are more "human-like" and have to do with their character. Some of the characteristics present in "Personality" are not cluster related or are not linked with the data analysis we performed on the survey. We will now discuss the aspects of Personality which are cluster related.

Personality includes the factors discussed in Section 4.1.2. They are as follows:

- Friendliness - Willingness to travel with other people
- Susceptible - how accepting the user is regarding incentive policies
- Transport - associates the use of private transport with money spent on fuel and on public transport
- Urban - relates travel distance and money spent on public transport
- Willing - users with a high value (close to one) generally share their commuting trips. It means the user is very open to share their rides with anyone, but especially with people they have some level of trust with.

The cluster defined variables are explained in more detail in this section, while the rest are detailed in Chapter 5 Section 5.2. Cluster defined variables are characteristics that are determined by the cluster the user belongs to, following the distribution that characterizes the members of the cluster.

First we need to allocate each user to a cluster. The percentages of the clusters represented in our population came from the survey results. The chart in Figure 4.10 shows the representation of each cluster found in our dataset.

After assigning each user from our dataset to the corresponding cluster, we were able to better characterize the users belonging to each cluster. To create new users for our synthetic population we need both general information that pertains to the population (Section 5.2) and also information more cluster specific.

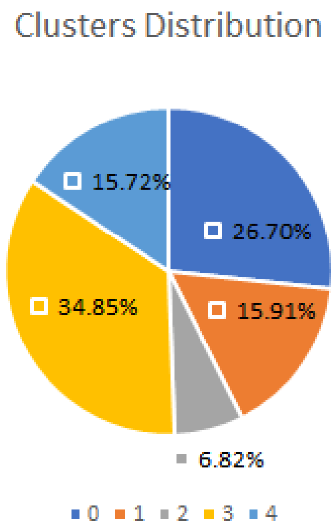


Figure 4.10: Clusters Distribution

The information we need from each cluster is:

- Distance from destination
- Ratio of private vehicle ownership
- Available seats
- Probability Distribution for each of the factors - Friendliness, Susceptible, Transport, Urban and Willing

The process of finding out the ratio of private vehicle ownership and available seats was simple. From the survey we had, for each user if they had a private vehicle and, if they were owners, how many seats did they usually have available. The number of available seats ranged from 0 to 6. We built a table to organize the information for each cluster, which is depicted on Table 4.2. The ratio of private vehicle ownership for each cluster consisted of seeing how many users from that cluster have a vehicle and dividing by the total cluster members.

Table 4.2: Seats Probabilities for all clusters

Clusters	Seats						
	0	1	2	3	4	5	6
0	0.71%	14.28%	0%	7.14%	75.71%	1.43%	0.71%
1	0%	21.62%	5.41%	10.81%	62.16%	0%	0%
2	5.56%	5.56%	0%	11.1%	72.22%	5.56%	0%
3	37.50%	25.00%	0%	25.00%	12.50%	0%	0%
4	0%	11.90%	7.14%	2.38%	78.57%	0%	0%

Regarding both distance from the destination and the probability distribution for each of the factors, the process was different and required a bit more work. We decided that, since we are working with continuous variables, the best way was to find a known probability distribution, such as, a Normal Distribution [Weisstein, 2019a] or a Laplace Distribution [Weisstein, 2019b], that best matched the distribution from our dataset. A list of the available distribution functions is available here [Scipy Community, 2019].

In order to evaluate and discover which known probability distribution best fitted our data, we used the Kolmogorov-Smirnov Goodness-of-Fit Test from Scipy [Scipy Community, 2014]. The Kolmogorov-Smirnov Test [KST, 2008] is used to decide if a sample follows a specific distribution, according to the p-value it returns. The null-hypothesis of this test is that the empirical distribution and the known distribution are identical which means that, the lower the p-value, the greater the confidence we can have that the distributions are not identical. If the p-value is greater than our threshold, (example a p-value of 0.05 means that we have a 5% chance of rejecting the null hypothesis), then that means that the distributions may be identical and we can then look at the other value returned from this test, the D statistic. The D statistic represents the max distance between the Cumulative distribution function [CDF, 2014] of the two distributions. The closer this number is to 0, then the more likely it is that the two distributions are identical.

Comparing our empirical distribution against the known distributions available in the Scipy module [Virtanen et al., 2020], we were able to find the distributions to represent each of the factors and the distance from the destination.

After knowing the distributions, we placed some limits regarding the minimum and maximum values of the variables. Regarding the distance variable we limited the minimum distance to 1km and the maximum distance to 30km. In respect to the value of the factors, the limits we placed were that the value had to be between 0 and 1.

4.3 Chapter Summary

In this chapter we first started by presenting the data we had collected through a survey.

After taking a better look at the data, we applied the factor analysis method which enabled us transform our dataset and consequently apply the K-Means clustering algorithm in order to divide our dataset into clusters. After forming clusters we learned about how these divided our dataset and the general characteristics of user's belonging to each cluster.

Lastly we described how we built the agents belonging to the artificial society, what the user's characteristics are, the distributions they follow and how they were obtained.

Chapter 5

Proof Of Concept

In this chapter we present our case study and make a detailed analysis of the data used to generate our artificial society. We describe the missing user characteristics from Chapter 4, characteristics of the transport services and the matching algorithms created for those services. Each service has travelling restrictions, e.g. distance restrictions, that limit the users that can benefit from them. Lastly we present the utility function used in the reinforcement learning algorithm by our agents.

5.1 Case Study

FEUP is an engineering faculty in Porto which has a lot of members belonging to it including teachers, students and researchers. In this description we are putting more focus on Teachers and Students. Teachers and Students belong to different departments depending on the degree they are pursuing (students) or the degree that they have (teachers).

First of all we must state why FEUP is a closed community, since that is the focus of our work. FEUP is considered a closed community since:

- Members don't change that often ;
- Members go to and leave from the destination at similar times, which makes it easier to match people for carpooling for example (because of the classes schedule);
- Members of closed communities are more likely to trust each other, due to their proximity and interaction history.

Trusting relationships can be formed between students, teachers and even between students and teachers, depending on the interactions they have. These relationships are important since they influence with who people prefer to travel. Example if you used a car to get to FEUP and you had an extra place, you are more likely to offer that place to your friend instead of a stranger.

There are various methods everybody can use to reach the faculty, which are:

- Public Transport: examples are train, metro and bus

- Private Transport: in this category we are talking about cars and motorcycles
- Walking
- Bicycling

Important aspects to take into consideration when using Private Transport are where to park your vehicle and, when using electric vehicles, you may also want to know where to charge it. FEUP has a parking lot for students and teachers/other personnel and some specific locations to park motorcycles and bicycles safely. Regarding the charging of electric vehicles, the faculty also provides charging stations, though not widely available. The faculty also provides a bicycle renting service. Students and other personnel can rent a bicycle during the school year, free of charge, as a greener way to travel.

In order to have Community MaaS some changes would have to be made such as the creation of a platform which would integrate multiple transportation services such as bus, train, ride-sharing and also other services such as the parking and charging service. That platform would be capable of creating a single trip that would make seamless the interactions between the modes of transportation and the services. Its use would also need to be intuitive and easy to use to promote adherence.

Anyone from FEUP needing to travel to it can therefore:

1. Use Public Transportation: Bus, Train, Metro
2. Use Private Transport: Car, Motorcycle
3. Walk
4. Use a Bicycle: use their own privately owned bicycle
5. Rent a free bicycle from the university
6. Ride-share

Methods 5 and 6 are the least used. Method 5 is less known and it's more limited (since there is only a limited number of bicycles) while Method 6 requires additional work in comparison with the other single methods.

Ride Sharing would be the way of travel which needs more work since it requires coordination between multiple users. This method is also the one that is most influenced based on the relations between the users, in comparison with the others.

When talking about travelling to an organization like FEUP, where the members travel to it extremely frequently, we stop talking about individual trips and focus more on the commuting aspect. We can compare a trip to the nearest shopping mall with a trip to faculty. They both boil down to being going from point A to point B, but since going to the shopping mall is something that happens a lot less regularly there is generally more diversity, while commuting implies a routine, which people do not really change.Example is if someone lives far away and uses public transportation, they usually stick to that routine all year round.

With the option of Ride Sharing in a platform available to all the students and teachers of the faculty, the user would have potentially more choices then he knew he had. Using Subscription mobility packages would also potentially lead to people trying other modes of transport. A perk of having such a platform available would be that if anything happened to one of the transports used in their routine, such as a strike, the platform would make the task of searching for an alternative much easier.

5.2 Artificial Society - User General Characteristics

Agents in our society have multiple characteristics, some which are derived from the cluster they belong to and some which are more general. In Chapter 4 Section 4.2 we discussed the cluster specific characteristics and their distributions. In this section we are going to focus on the general characteristics, enumerate them and see how they are attributed to the users.

The list of general characteristics are:

- Cluster - already explained in Chapter 4 Section 4.2
- Course - one of nine
- Year - which year the student is enrolled into (from one to five)
- Start Time - the desired time to leave his house and go to the destination
- Income - money received from work or other investments
- Budget - percentage of income allocated to transportation
- Has Bicycle - indicates if the user owns a bicycle or not
- Personality - characteristics that represent a more human side of the user
- Friends - a list of other users with which the user has a trusting relationship with.

Regarding what we titled "Personality", it has multiple factors used to characterize the users which are more "human-like" and have to do with their character. Personality has general characteristics, which are explained in this section, and cluster specific characteristics that were discussed in Chapter 4 Section 4.2.

The general characteristics are:

- willingness_to_pay - measures how much emphasis the user puts on the cost, users with more willingness_to_pay are more likely to pay more in return of waiting less or having more comfort for example.

- willingness_to_wait - measures how much emphasis the user puts on the time spent commuting, users with more willingness_to_wait are more likely to wait more in return of a lower cost for example.
- awareness - measures how environmental aware the user is, users with more environmental awareness are more likely to choose a more environmental aware mean of transport even if it has a greater cost or more waiting time for example.
- comfort_preference, measures how much emphasis the user put on the comfort of the commute, users with more comfort_preference are more likely to choose means of transport with more comfort even if it has a greater cost or more waiting time for example.

General characteristics are not defined by the cluster the user belongs to but are determined from the general population and are equal for every agent.

We will now present the origin of these characteristics and how to attribute them to the user.

Course and Year

The distribution of courses and years comes, not from the survey, since it could be biased to our small dataset, but from the faculty.

Since there are a lot of courses available at Faculty of Engineering of the University of Porto, we decided to select the integrated masters courses and their years' distributions to have more variety in our population. Table 5.1 shows distribution of courses and years.

Table 5.1: Integrated Masters Statistics

Course	1º Year	2º Year	3º Year	4º Year	5º Year
MIB	74	80	77	85	93
MIEC	160	152	142	145	170
MIEA	41	32	29	29	57
MIEIG	85	88	96	87	99
MIEEC	224	233	193	218	295
MIEIC	159	175	173	147	193
MIEM	187	173	196	189	276
MIEMM	26	32	26	31	31
MIEQ	77	70	66	79	98

These values were then used for our agents.

Start time

The start time of a User represents the time he would prefer to leave his house for his destination, such as we also have a time we prefer to leave our house, which is different for every person. This time is derived from a normal distribution defined by the designers of the system. For example the distribution parameters we use later on in our experiments are depicted in Figure 5.1, which is a normal distribution with mean 8 and standard deviation 2.

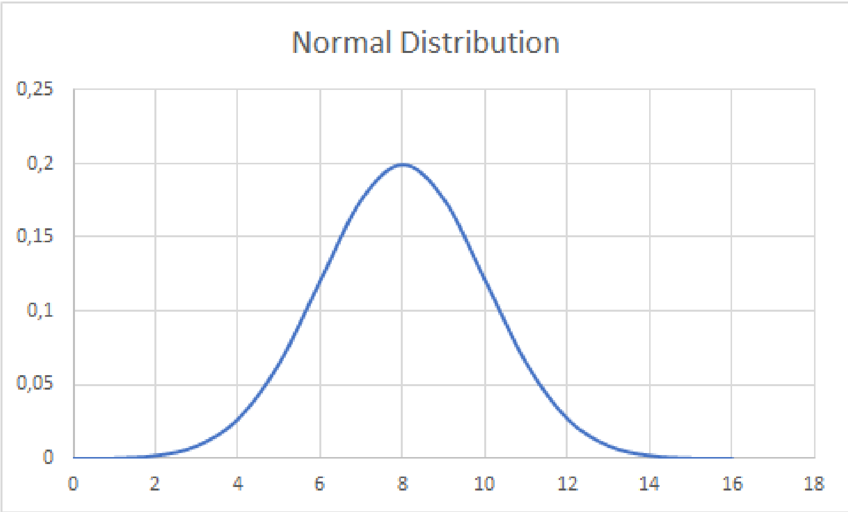


Figure 5.1: Start Time Distribution

This distribution represents the rush hour/time window that exists every day because of the people trying to get to work or school, causing traffic and delays. The concept of using such a distribution to simulate traffic was inspired by Cruz' et al work [Cruz et al., 2019].

Income, Budget and Willingness to pay

We have grouped these three characteristics together since they are all connected. First off income is the money the user receives through their work. Since we did not have access to that information we decided to use a distribution that represents the payment for workers in continental Portugal divided in three tiers - less than, equal to or more than minimum wage.

Figure 5.2 from Gabinete de Estratégia e Planeamento [GEP do MTSSS, 2019] represents those divisions into tiers throughout the years of 2010 until April 2019.

Using this information, we discovered which known probability distribution best fitted it using the Kolmogorov-Snirnov Test [KST, 2008] and then attributed a value from that distribution to our user.

Figure 5.3 represents the salary distribution of our population (in euros).

With income information the next steps were attributing a value for budget and willingness to pay of the user.

According to INE and PORTDATA[INE and PORDATA, 2020] , in 2017, 15.9% of peoples income was spent on transport and communications while according to Garcia's work [Garcia, 2020] from 2020 the author states that in 2019 almost 13.4% of Portuguese families income was spent on transportation alone. Keeping these articles in mind we reached the conclusion that 14% of their income would be allocated towards transports.

Lastly we have Willingness to Pay. Willingness to pay is a value, from 0 to 1, derived from the budget, the higher the budget, the higher the willingness to pay.

Tabela 8. Distribuição dos trabalhadores por escalão de remuneração em Portugal Continental, 2010-2019

		RMMG (€)	p<RMMG	p=RMMG	p>RMMG
ano	2010	475	8,4%	13,2%	78,4%
	2011	485	7,9%	13,9%	78,2%
	2012	485	7,4%	13,5%	79,2%
	2013	485	7,4%	13,1%	79,5%
	2014	485/505	7,7%	14,1%	78,2%
	2015	505	8,1%	17,4%	74,5%
	2016	530	7,6%	20,6%	71,8%
	2017	557	7,8%	22,0%	70,2%
	2018	580	7,8%	21,7%	70,5%
janeiro a abril	2010	475	9,3%	13,1%	77,6%
	2011	485	8,4%	13,6%	78,0%
	2012	485	7,5%	13,3%	79,2%
	2013	485	7,3%	12,9%	79,8%
	2014	485	7,4%	12,8%	79,9%
	2015	505	8,4%	17,3%	74,3%
	2016	530	8,1%	20,9%	71,0%
	2017	557	8,1%	22,9%	69,0%
	2018	580	8,0%	23,0%	69,0%
	2019	600	8,1%	22,4%	69,6%

Fonte: Instituto de Informática, IP (com base nas DRSS)
Nota: Dados sujeitos a alterações

Figure 5.2: Salary Tier distribution

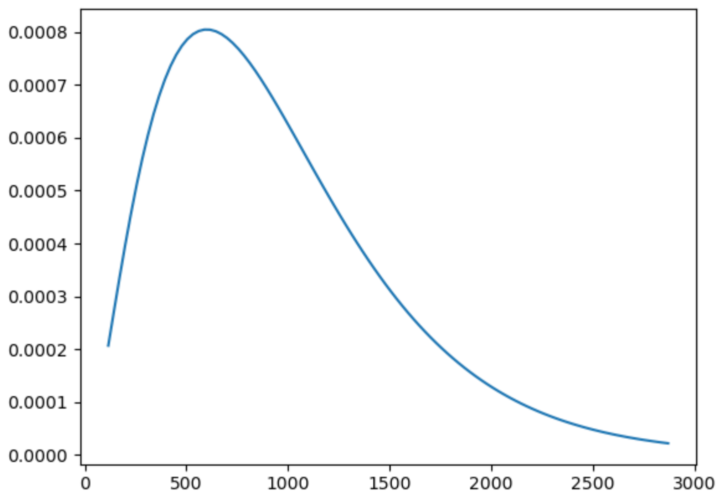


Figure 5.3: Salary Distribution (in euros)

We know that just because someone technically has more money to spend on transportation services it does not automatically mean that they are more willing to spent it, but we decided to make this assumption in order to simplify the complexity and diversity of the human nature.

Has Bicycle

A User may or may not have a bicycle which he can use to travel to his desired destination. Unfortunately this information was not part of the survey so, to simplify, we decided on an ownership percentage.

Willingness to wait, Awareness and Comfort Preference

Information regarding distribution for these variables is hard to find and differs a lot from country to country and between age groups so, for all these variables, we decided to simplify them and use a normal distribution with mean 0.5 and standard deviation of 0.3. All these variables have values between 0 and 1.

We have now finished the specification of the agents from our synthetic population.

5.3 Transportation Services Characteristics

The means of transportation we are taking into consideration are: Private Vehicle, Public Transport, Ride Sharing, Bicycle and Walking.

Regarding the Private Vehicle we decided to use a diesel powered car as our representative while for public transport we decided to use natural gas powered buses.

We will now present the characteristics for each of the modes of transport:

5.3.1 Private Vehicle

- Cost - 0.72 € per km
- Comfort - 1
- Awareness - 0.2
- Emissions - 139 gCO2/km
- Transport Subsidy - 0.36 € per km
- Credits - 0
- Speed - 50 km/h

While we were able to find references for the variables of CO2 emissions, in the work from Hill et al., [Hill et al., 2019], and transport subsidy in two documents from Ministério das Finanças e Administração Pública [Ministério das Finanças e da Administração Pública, 2008] and [Ministério das Finanças e da Administração Pública, 2010], the same cannot be said for cost. Knowing how much is the cost of using a private vehicle, in our case a diesel car, per kilometer, has a lot of variables and indirect costs that we usually do not think about, but that have to be taken into consideration. We decided to use a value of 0.72 € per kilometer, which is twice the value of transport subsidy, to generalize and simplify. To check if this simplification is acceptable we tried to compile a list of costs and see what would be the costs in an hypothetical situation.

The costs found are:

1. The cost of buying the vehicle - either in full or in monthly installments
2. Single Vehicle Tax/Single Road tax
3. Insurance
4. Vehicle Inspection
5. Repairs/Check Ups - such as new tires and oil changes
6. Tolls
7. Fuel
8. Depreciation

All of the items enumerated have to be taken into consideration when calculating cost per km, even though most of the time, when thinking about the cost of a car trip, we only take into consideration direct costs such as money spent on fuel and on tolls.

It's worth to mention in particular the depreciation cost. Depreciation rates depend on the vehicle, brand, age and also mileage, which makes it harder to generalize. Storchmann [Storchmann, 2004] states that geometric depreciation appears to be a good approximation to real depreciation prices and the average depreciation rate in OECD countries if 31%. Figure 5.4 illustrates the value of used automobiles using the vehicle's ages and we can see the difference between an OECD country and non-OECD country.

We now present an hypothetical scenario to check how much would the cost per kilometer would be.

Scenario: Brand new 25 000 € car and it makes 1500km each month.
If the depreciation rate is of 30%, using the initial value in the first year, this means that it depreciated 7500 € in a year.

Dividing 7500 € by 12 months it means it depreciated 625 € per month which brings the cost to 0.42 € per km. Using an average of the top 3 cars sold in 2019 in Portugal the average consumption is of 5.1l/100km, using diesel prices of 1.425 € per liter, that results in a cost of 0.07 € per km.

If the car is used for 7 years that brings the total cost to 3571.43 € per year, 297.62 € per month, which results in 0.20 € per km.

With a Single Vehicle Tax of 150 € per year ([Assembleia da República, 2007], [Assembleia da República, 2020]), that makes 12.5 € per month, which is 0.008 € per km.

Average inspection prices amount to 35 €, which adds more 0.002 € to our total. It's important to notice depending on the age of the car this added cost of 0.002 € may not happen every year.

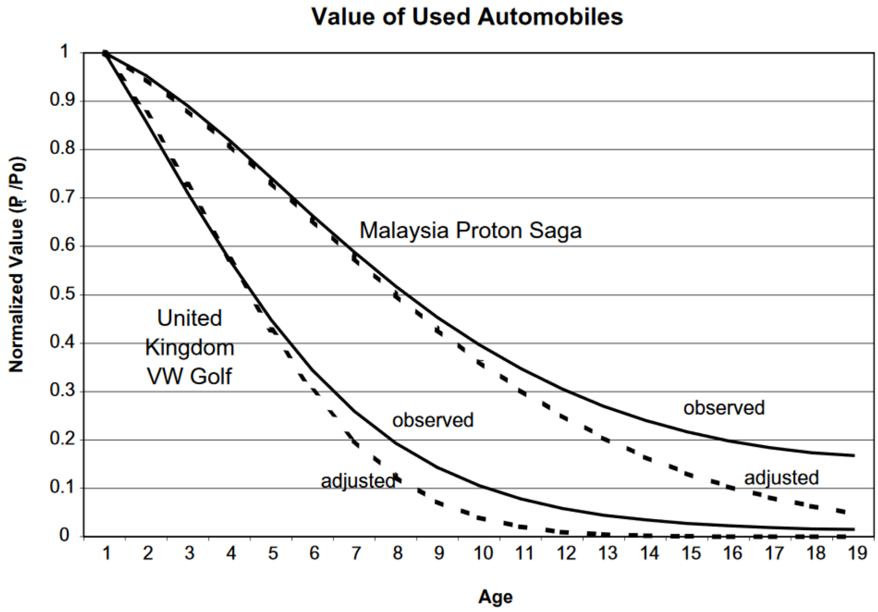


Figure 5.4: From [Storchmann, 2004]

Regarding insurance, using the price of 220 € per year, that adds 0.01 € per km which gives a total of 0.71 € per km. This cost of 0.71 € per km however does not include any tolls or possible repairs/maintenance checkups.

We conclude that the simplification of 0.72 € per kilometer is plausible and satisfactory.

5.3.2 Ride Sharing

- Cost - 0.72 € per km
- Comfort - 0.6
- Awareness - 0.5
- Emissions - 139 gCO2/km
- Transport Subsidy
  - 2 users - 0.144 € per km
  - 3 or more - 0.11 € per km
- Credits - 1
- Speed - 50 km/h

The cost is the same as the Private Vehicle cost, since we are considering a diesel fueled car for both. All the costs associated with the trip, whether it be from the path or from parking and tolls, are split evenly between driver and riders.

Regarding the transport subsidy we found this reference to a Decree-Law that stated transport subsidy values for workers travelling together in a rented vehicle that differed between the total number of workers. We used these values to just shared vehicles instead of them having to be rented. The original values stated in document Portaria n.º 1553-D/2008 [Ministério das Finanças e da Administração Pública, 2008] where later modified in Decreto-Lei n.º 137/2010 [Ministério das Finanças e da Administração Pública, 2010] which brought them to the values used in our work.

5.3.3 Public Transport - Natural Gas Bus

- Cost - 0.22 € per km
- Comfort - 0.4
- Awareness - 0.9
- Emissions - 62.5 gCO2/km/passenger
- Transport Subsidy - 0.11 € per km
- Credits - 3
- Speed - 50 km/h

Finding a value for cost per kilometer for public transport can also be a bit tricky since it depends on the type of ticket the user buys, which can be a single use ticket or a monthly pass, on the age of the user and his employment status. Another variable is also the amount of zones you can use your ticket in, which gets more expensive the more zones you have access to.

We decided to simplify the cost value , using the value of transport subsidy as a reference, and using twice that value, similarly to how we decided the value for the cost of the private vehicle.

In regards to the CO2 emissions, we found the value of CO2 emissions for urban CNG emissions in a document from the European Environment Agency [European Environment Agency, 2019] and, used a value from the work of Hill et al., [Hill et al., 2019] which is the average passenger occupancy of a London bus to obtain the CO2 emissions per passenger. We use that value since, even if the bus passengers are not all members of the organization, the emissions produced by that bus are still being shared between the passengers.

Important info about public transport is that they have schedules and routes. We created routes to ensure that all buses pass through every node in our graph, to make public transport available to everyone. Buses are running from midnight to 16h, following a normal distribution with mean 8 and standard deviation of 2, illustrated on Figure 5.5. That distribution also represents the users start time and gives us an idea of how the users are distributed across time. There is one bus in every route every 30 minutes and, when within the time window between $mean - standard\ deviation$ and $mean + standard\ deviation$, buses come every 10 minutes.

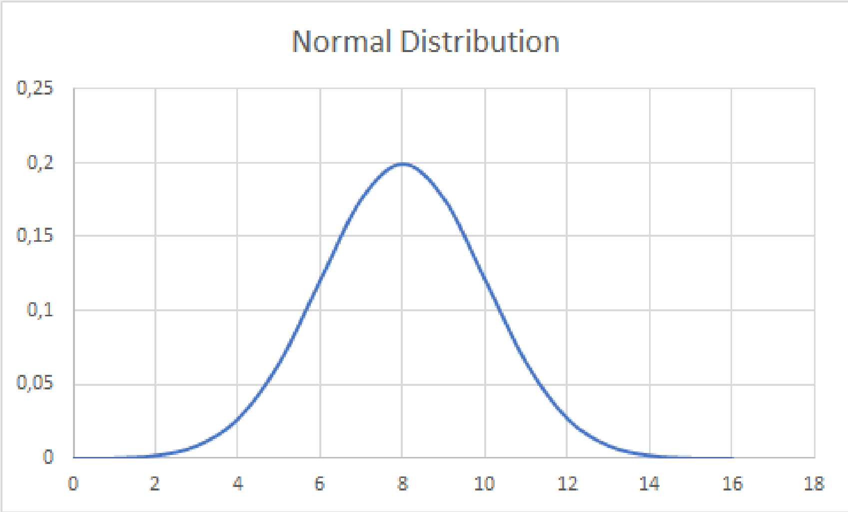


Figure 5.5: Normal Distribution followed by the Users

5.3.4 Bicycle

- Cost - 0 €
- Comfort - 0.5
- Awareness - 1
- Emissions - 0 gCO2/km
- Transport Subsidy - 0 € per km
- Credits - 5
- Speed - 20 km/h

Bicycles are one of two of the most environmentally friendly options taken into consideration in our work. We are considering a regular bike instead of an eletric bike and that's why the cost is zero, else we would need to account for the charging cost.

Besides the speed being lower than the speed of engine powered vehicles, another restriction for this service is that only those living within 5 km of the destination can use this service. This restriction was imposed based on the 85th percentile from Larsen et al.,[Larsen et al., 2010], when taking into consideration the purposes of working and going to school. 5km is a distance that the average person can comfortably travel, especially when talking about commuting, which is done everyday.

5.3.5 Walking

- Cost - 0 €

- Comfort - 0.5
- Awareness - 1
- Emissions - 0 gCO2/km
- Transport Subsidy - 0 € per km
- Credits - 5
- Speed - 5 km/h

Walking is one of the two most environmentally friendly options taken into consideration in our work. Walking is also our slowest option, at 5km/h while the other clock in at 50km/h and 20km/h.

One restriction imposed for this service was that only those living within 2km of the destination can use it, since it's the average distance observed in Larsen et al., [Larsen et al., 2010], based on the 85th percentile, that the average person can walk everyday to get to the destination, when focusing on work and school purposes. Authors Keijer and Rietveld [Keijer and Rietveld, 2000] also support this distance by saying that for trips up to 2km the preferred method is walking.

5.4 Matching Algorithms

In this section we will explain in more detail the matching algorithms and traveling restrictions of each way of travelling.

5.4.1 Private Vehicle

In regards to private vehicle, we do not have a matching algorithm in place. To use this service the only pre-condition that exists is that the user needs to own a private vehicle. Ownership of private vehicles differ between clusters.

5.4.2 Public Transport

Public Transport matching refers to allocate agents to buses that pass through the agent's house , taking into consideration the agent's time preferences. The algorithm used to match agents to buses is described in pseudo-code in Algorithm 0.

Agents that end up not being matched, either because the time chosen to leave their house and the time they are willing to wait does not match up with any of the buses schedule or because the buses are full, do not travel to the destination. Instead what happens is that they get a negative value for their utility related to the action they chose, use public transport. We decided that the real world situation equivalent is when agents stay home instead of going to classes and they miss some important information that would be on the exam.

Algorithm 1 Public Transport Matching

```
procedure PUBLICMATCHING(users, buses)
    for all user,users do
        possible_buses ← CheckBusesPassUserHouse(buses)
        for each bus in possible_buses do    ▷ Checks the possible time the user would need to wait for that bus.
            wait_time ← abs(BusSchedule(user.house) − user.time)
            if wait_time < (user.willingness_to_wait ∗ MAX_WAITING_TIME) then
                                             ▷ Allocates user to bus if it's within the time window, has available seats and has the least waiting time.
                if Bus_Has_Available_Seats and Is_Faster_Bus then
                    user_bus ← bus
                end if
            end if
        end for
    end for
end procedure
```

5.4.3 Ride Sharing

Ride Sharing matching refers to the pairing of multiple agents in the same vehicle, owned by the driver of the vehicle. Contrary to public transport, which has a fixed schedule, ride sharing is more unpredictable and changes everyday, since it depends on the users who decide to use this service that day. Another fact to consider is the disposition of our graph. Since we have directed edges, there are less paths between users which makes it even harder to match agents with each other. There are no extra incentives for the driver agent to pick up other agents, except the division of travel costs.

The algorithm used to match agents is described in Algorithm 0.

5.4.4 Bicycling

In regards to bicycling, we do not have a matching algorithm in place. To use this service the only pre-condition that exists is that the user needs to own a bicycle and live within the designated distance (5km).

Ownership of bicycles for the entire population is of 30%.

5.4.5 Walking

In regards to walking, we do not have a matching algorithm in place. To use this service the only pre-condition that exists is that the user needs to live within the designated distance (2km).

Algorithm 2 Ride Sharing Matching

```
procedure RIDESHARING(users)
    drivers ← CheckUsersWhoOwnCar(users)
    while NumDrivers > 0 do
        driver = GetNextDriver(drivers)
        possible_routes = CheckAllRoutesDestination(driver, node)
        possible_riders = GetAllUsersInRoutes(users, possible_routes)
        for all rider, possible_riders do    ▷ Check if user is accessible to driver and their schedules match. Add user to possible pickup list
            if RiderAccessible and InTime(rider, driver) then
                possible_pickup.AddRider(rider)
            end if
        end for
        chosen_rider = ChooseRandom(possible_pickup)    ▷ Pick one of the available riders
        pickup.append(chosen_rider)    ▷ Add rider to the driver's pickup group
        while driver.hasAvailableSeats and driver.NotReachedDestination do    ▷ Checks users that the driver can pick up, starting from the selected rider's house
            pickup = CreatePickup(rider_node)
            chosen_rider = ChooseRandom(possible_pickup)
            driver.pickup = pickup    ▷ Get the rest of the users to pickup along the way.
        end while
    end while
end procedure
```

5.5 Utility

5.5.1 Utility Factors

Each user will receive an utility value every time he chooses one of the transportation services, that value will then be stored and used in the learning algorithm so that the user learns which service is the best for it's needs.

When thinking about choosing a mode of transport some aspects come into mind like time, price, comfort, accessibility. Schedule flexibility, cost, safety and time are important factors mentioned in the work from Tischer and Dobson [Tischer and Dobson, 1979] that users take into consideration when choosing or switching from one mean of transport to another. In the work from Levin [Levin, 1982] important factors studied mentioned are comfort, convenience and cost when comparing between driving alone or ride sharing. Taking those mentioned factors into consideration the aspects we incorporated into our work were comfort, cost and time. We also have an awareness factor which represents the environmental awareness of the transport used, how close it is to 1 determines how environmentally friendly it is. Nowadays we want to bring more awareness to the environmental impact we have when choosing how to go to work or school so that's why we incorporated that factor.

5.5.2 Utility Function

We designed an utility function for our work based on the work of Kokkinogenis et al., [Kokkinogenis et al., 2014], to quantify how good a travelling service is according to certain characteristics.

Our utility function is illustrated in Equation 5.1. It's a simple function were we just add the utility for each of the factors we mentioned previously in Section 5.5.1. All the individual components have a value between 0 and 1.

$$U_{Total} = U_{Cost} + U_{Time} + U_{Environmental} + U_{Comfort} \tag{5.1}$$

The utility function has all the factors we determined important in Section 5.5.1. Now we will explain every segment of the utility function.

We begin with the Cost utility segment, depicted on Equation 5.2.

$$U_{Cost} = -\frac{1}{5 * willingness_{pay}} * \frac{cost}{MAX\_COST} + 1 \tag{5.2}$$

The variable cost represents the cost of the trip, including parking, the user needs to pay. We use a variable MAX_COST that represents a very high trip cost, that is difficult to get to, in our scenarios with our configurations. We use that value in order to normalize the Cost Utility component.

Next is the Time utility segment, illustrated in Equation 5.3, which has a similar thought process to the Cost segment, but dedicated to total travel time. Total travel time includes both the travel time, which is the time spent on route to the destination, and the waiting time. Waiting time is generally different than 0 when using the public transport and ride sharing services.

$$U_{Time} = -\frac{1}{5 * willingness_{wait}} * \frac{time}{MAX\_TIME} + 1 \tag{5.3}$$

The following segment from the utility function, depicted in Equation 5.4, refers to the environmental concerns. This segment simply relates the transport_awareness , which is a value belonging to the transportation service that shows how environmentally friendly the service is, from 0 to 1, with the awareness variable which is specific to the personality of the user. Awareness represents the importance that the user gives to the impact of his carbon footprint and how that influences his transportation choices.

$$U_{Environmental} = transport_{awareness} * awareness \tag{5.4}$$

The last segment refers to comfort segment. It relates the transport_comfort, which is a value from the transport service that indicates how comfortable trips generally are, with how important comfort is to the agent Comfort is something very hard to measure since for some using public transport may be uncomfortable because it's too crowded, with long waiting time and extra stops along the way, but for others it may be more comfortable than driving since it's less stressful and cheaper. It depends on personal preferences since each service has their advantages and disadvantages [Beirão and Sarsfield Cabral, 2007]. In our scenarios we decided on private vehicle being the most comfortable and public transport the least comfortable.

Equation 5.5 illustrates the comfort segment of the utility function.

$$U_{Comfort} = transport_{comfort} * preference_{comfort} \tag{5.5}$$

Cost, time, transport awareness and transport comfort are the values from the chosen transportation method, described in Section 5.3, while $\text{willingness}_{\text{pay}}$, $\text{willingness}_{\text{wait}}$, awareness and $\text{preference}_{\text{comfort}}$ are values from the User mentioned in Section 4.2. These factors are shown here all together in a single function, however they can also be considered as individual factors with possibly different weights and value to the decision.

5.6 Chapter Summary

In this chapter we started by presenting our case study, followed by the description of the users' more general characteristics and the distribution they follow. Next we described the characteristics of the mobility services and the matching algorithms created for the public transport and ride sharing services.

We closed this chapter with a detailed presentation of our utility function and all the components that make it up.

Chapter 6

Experiments and Results

The purpose of this chapter is to instantiate the proposed meta-model and conduct several experiments with different incentive policies. Such experiments allow for the evaluation of the impact those policies may have in regards to the travelling behaviour of the commuter agents. We first start by presenting the common setup for our experiments. A description of the simulation scenarios to be explored are then detailed. Lastly we present and discuss the results of our simulations.

6.1 Initial Setup

For our scenarios we created an initial population of 800 agents. This population was then used for all of the scenarios, in order to provide consistency and to facilitate comparison between different incentive policies. Bicycle ownership ratio was 30%. The period of the Public Transport service is dependent on the time of day and is defined by the following equation:

$$T = 10 \; if \; t \in [\mu - \sigma, \mu + \sigma]$$
$$T = 30 \; if \; t \notin [\mu - \sigma, \mu + \sigma]$$

where

$$\begin{aligned} T &= \text{Time period of the public transport} \\ t &= \text{Current time} \\ \mu &= \text{Peak time of the distribution} \\ \sigma &= \text{Standard deviation of the distribution} \end{aligned} \tag{6.1}$$

Peak time is 8am, with a standard deviation of 2h so this mean that between 6.00am and 10.00am the buses would come every 10 minutes. Every scenario was ran 3 times with 3000 repetitions each, which would simulate an observation period of 3000 days in the community.

We will now present the multiple experiments we performed throughout this work.

First off we had to test multiple utility functions and choose the one that seemed most suitable according to the results. The second task at hand was to test out which learning technique was the most suitable for our work. The choices were between having a single objective utility function or using ensemble learning. While using both the single objective function and ensemble learning we tested out a number of techniques. Those techniques would either have a general/group approach or a more individual approach.

In regards to general or group approaches we have the following:

- Have a single neural net that would learn with the experiences of all the members of the population;
- Using ensemble learning, have 4 neural networks, each taking into consideration one of the segments of the utility function, that learn and decide for all the agents;
- Have a neural net for each of the 5 clusters. Each neural net would learn with and choose the service only for agents belonging to that cluster;

While in individual approaches we have:

- Have a neural net,for each agent, that would dictate the service for that agent;
- For each agent, use the weighted average utility of the past 200 experiences for each available service to determine which service to choose;
- Use ensemble learning where each user has 4 learning agents, each taking into consideration one of the segments of the utility function, and use the average of the past 200 experiences for each service to determine which service to choose.
- Use ensemble learning where each user has 4 learning agents, each taking into consideration one of the segments of the utility function, where each use a neural net to decide and vote on the best service.

Lastly, after having chosen the utility function and learning technique, we carried out our simulation scenarios.

6.2 Simulation Scenarios

In our work, in order to study the impact that different incentive policies can have if applied in the context of closed communities, we devised and implemented various different simulation scenarios.

The simulation scenarios are:

1. Descriptive Scenario
2. All Private Vehicle

3. All MaaS services
4. All mobility solutions
5. All mobility solutions but with small parking fee
6. All mobility solutions but with high parking fee
7. All mobility solutions but with travel credits
8. All mobility solutions but with social travel credits

We will now discuss each scenario more in depth starting with Scenario 1.

6.2.1 Scenario 1

Scenario 1, the Descriptive Scenario, uses the percentages of each mode of transport used, directly from the survey, without any change. This scenario represents how the population was acting, and the transport choices they were taking, at the time of the survey.

This scenario is used to represent how the surveyed answer. The users choose a service based on the percentages we obtained from the survey, separated by cluster and distance from destination. Tables 6.1, 6.2, 6.3, 6.4 and 6.5 represent the distributions of services for each cluster based on distance from destination. The value NA stands for Not Available since we do not have instances of members of that cluster living in those distance intervals.

Table 6.1: Cluster 0 Original Choices probabilities

Services	Distance from Destination						
	[0-1]	]1-3[	[3-5[	[5-10[	[10-20[	[20-30[	30+
Private Vehicle	0 %	47.06%	50%	69.70%	67.92%	75%	100%
Public Transport	0%	11.76%	33.33%	27.27%	32.08%	25%	0%
Bicycle/Walk	100%	41.18%	16.67%	3.03%	0%	0%	0%

Table 6.2: Cluster 1 Original Choices probabilities

Services	Distance from Destination						
	[0-1]	]1-3[	[3-5[	[5-10[	[10-20[	[20-30[	30+
Private Vehicle	0%	5.88%	11.11%	30.42%	25%	0%	0%
Public Transport	0%	29.41%	55.56%	65.22%	75%	100%	100%
Bicycle/Walk	100%	64.71%	33.33%	4.35%	0%	0%	0%

The users choose the service simply based on the percentages presented on the tables.

Table 6.3: Cluster 2 Original Choices probabilities

Services	Distance from Destination						
	[0-1]	]1-3[	[3-5[	[5-10[	[10-20[	[20-30[	30+
Private Vehicle	0%	0%	0%	37.50%	18.18%	50%	0%
Public Transport	0%	50%	100%	50%	81.82%	50%	100%
Bicycle/Walk	100%	50%	0%	12.50%	0%	0%	0%

Table 6.4: Cluster 3 Original Choices probabilities

Services	Distance from Destination						
	[0-1]	]1-3[	[3-5[	[5-10[	[10-20[	[20-30[	30+
Private Vehicle	0%	0%	0%	2.78%	0%	0%	NA
Public Transport	0%	29.82%	95.24%	97.22%	100%	100%	NA
Bicycle/Walk	100%	70.18%	4.76%	0%	0%	0%	NA

Table 6.5: Cluster 4 Original Choices probabilities

Services	Distance from Destination						
	[0-1]	]1-3[	[3-5[	[5-10[	[10-20[	[20-30[	30+
Private Vehicle	NA	NA	NA	NA	0%	10.53%	30.16%
Public Transport	NA	NA	NA	NA	100%	89.47%	69.84%
Bicycle/Walk	NA	NA	NA	NA	0%	0%	0%

6.2.2 Scenario 2

Scenario 2 represents our worst case scenario where every agent uses their private vehicle to commute to their destination. In this scenario none of the more environmentally friendly options such as Public Transport or Ride Sharing are available.This setting would provide us a way to see the performance of the system when saturated since every single agent would be on the road alone.

6.2.3 Scenario 3

Scenario 3 represents a situation in which every user abandons travelling alone in their private vehicle in favor of MaaS solutions, example Public Transport. This situation would show us the performance of the system when the MaaS services are saturated, a direct opposite of scenario 2.

6.2.4 Scenario 4

In Scenario 4, agents have all the mobility solution at their disposal, whether it be private transport or any MaaS service. This is more in tune with the real world and allows us to see how our population would be divided.

6.2.5 Scenario 5

In scenarios 1 through 4, when using either private vehicle or when ride sharing, it's free to park the vehicle, either it be inside or outside the organization's parking lot.

In scenario 5, agents have the ability to choose between all mobility solutions but we introduce the concept of a paid parking lot. The user's organization has a parking lot with a limited capacity and parking spots dedicated exclusively towards users who share their trip. Parking fees differ between travelling alone or travelling with others.

In this scenario we have a parking lot with total of 400 parking spaces (half of the total members of the organization), 200 of those spaces are reserved for shared vehicles which leaves the other 200 for private vehicles. Parking a shared vehicle is free of charge while a private vehicle costs 1€, if inside the parking lot, and 2€ outside.

6.2.6 Scenario 6

Similarly to scenario 5, scenario 6 also introduces the concept of a paid parking lot.

While in scenario 4 we had 400 parking spaces, half for members driving a private vehicle and the other half for members who ride share, we now present a harsher scenario. Here the parking lot now has a total of 200 spaces, of those 100 are for members who ride share and 100 are for the members who drive alone. When ride sharing the parking cost is 0 but when driving alone there is a fee of 10 €, while parking outside costs 12 € independently of driving alone or accompanied

6.2.7 Scenario 7

Scenario 7 represents a scenario in which the workers have the options of private vehicle and MaaS solutions at their disposal, but the difference is that we introduce the notion of travel credits.

The concept of credits and travel credits has been used in the literature in some works such as the one from Dogterom et al., [Dogterom et al., 2018], where they are used as an allowance to limit car use and Dogterom et al., [Dogterom et al., 2017] where credits are tradable between agents. We are using this concept and adapting it to our work. Travel credits serve as a type of currency that cannot be traded in for real money and does not have value outside this credits scheme, that can be traded in for prizes.

The users would all start with 0 credits. The way to gain credits would be by using MaaS solutions such as public transport and ride sharing. Each time a worker used one of those modes to get to the organization they would receive a certain amount of credits and eventually they would spend it in returns for discounts on those same modes.

The travel credits gained for each service are:

- Private Vehicle - 0
- Ride Sharing - 1
- Public Transport - 3

- Bicycle - 5
- Walk - 5

Those credits, each worth 0.05€, can only be spent to have a discount in Ride sharing and Public Transport, since using a bicycle or walking is free. Since the workers would have a discount on the more environmentally friendly options, this would hopefully incentivize workers towards those options. These credits would appear from contracts between the organization and the mobility providers and they would not add any extra costs to the organization.

6.2.8 Scenario 8

Scenario 8 represents a scenario in which the users have all mobility solutions at their disposal, which includes private transport and also MaaS solutions like public transport and ride sharing. The difference this scenario brings is the introduction of social travel credits.

The concept of travel credits was introduced in Scenario 6, the difference being that now, agents can share a percentage of the credits won with other users who are considered their friends.They share 10% of the credits gained with each friend, on the condition that the friend also chose a more environmentally friendly option, namely Ride Sharing and Public Transport. This way friends can share travel credits which may lead to using more environmentally friendly options. Sharing credits is also good since some users may not need to use their credits or have use for them but their friends may have.

6.3 Setting-up Results

We will now demonstrate the different experiments we conducted to select important elements for our simulation setup. First we decided on the utility function and then we determined which learning technique to use.

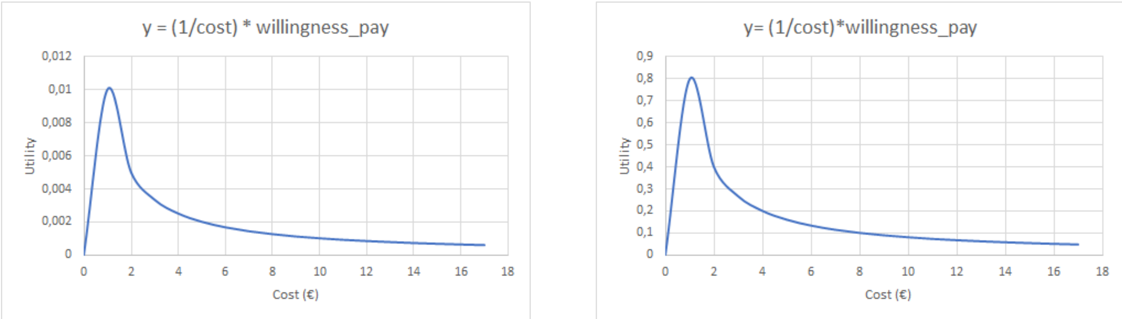
6.3.1 Utility Function Results

Throughout this work we tested a lot of different utility functions with different shapes e.g. linear and polynomial. The main idea of the function stayed the same as depicted in Equation 5.1 but the individual segments, namely the Cost and Time segments, are the ones that we experimented with. The initial function was based on the work from Kokkinogenis et al.,[Kokkinogenis et al., 2014] using the values of personality parameters such as $\text{willingness}_{\text{pay}}$ to personalize it.

The initial function, Cost and Time segments, are illustrated on Equations 6.2 and 6.3.

$$U\_cost = \frac{1}{Travel_{cost}} * willingness_{pay} \tag{6.2}$$

$$U\_time = \frac{1}{Travel_{time}} * willingness_{wait} \tag{6.3}$$



(a) Willingness Pay 0.01 (b) Willingness Pay 0.8

Figure 6.1: Initial Function Cost Curves

Figure 6.1 presents two graphs representing the graph curve for the Equation 6.2 when $willingness_{pay}$ is the minimum value (0.01) and when $willingness_{pay}$ has a high value of 0.8.

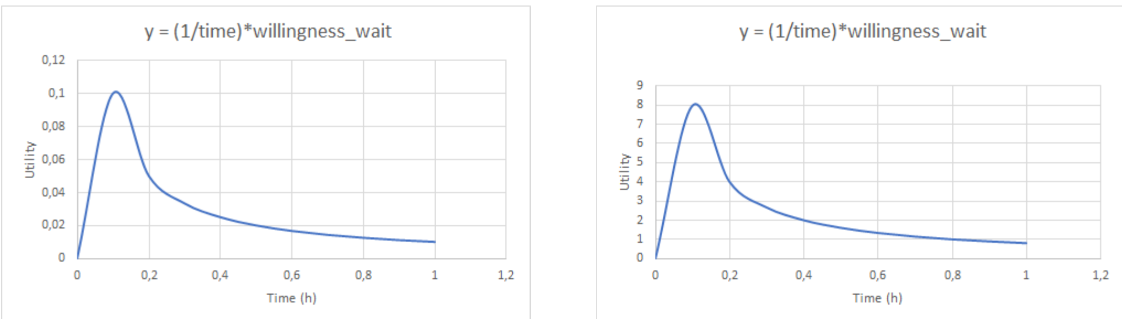
Figure 6.2 presents two graphs representing the curve for the Equation 6.3 when $willingness_{wait}$ is the minimum value (0.01) and when $willingness_{wait}$ has a high value of 0.8.

The curves of the functions helped us realize that these equations were not good enough for our work since either there was a sudden big difference between values (Figures 6.1 and 6.2 b) or there was not much of a difference (Figures 6.1 and 6.2 a) and that is not what we wanted.

We wanted to find a function where, when cost or time are 0, the utility is 1, since regardless of the monetary means you have or how patient you are, if one mode is free or it's instantaneous to arrive at the destination, then the utility in those parameters is max. The function should then decrease either faster if willingness is low and slower is willingness is high.

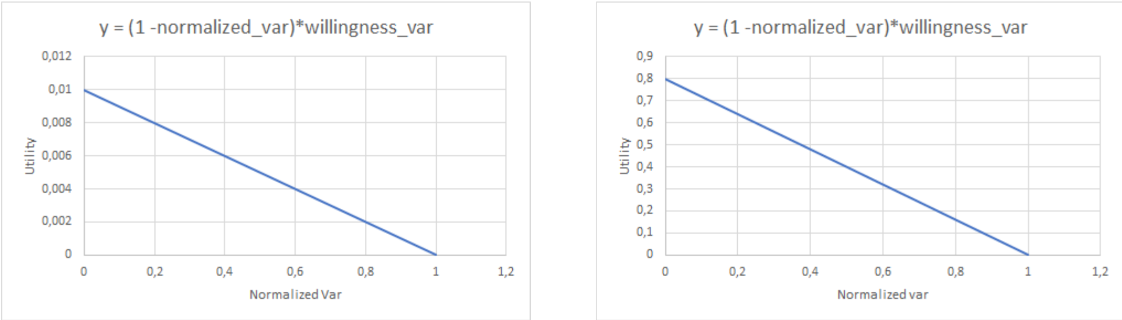
In the next function we tried to normalize the cost and time between 0 and 1. We decided that the Cost and Time segments would essentially be the same so they would be represented by the same curve. The resulting graphs are illustrated on Figure 6.3.

The function depicted on Figure 6.3 still does not meet our standards of the type of function we described before. While the decrease is better, the function still does not have the value of 1 in the initial point and when willingness is really high, even if the cost or time to get there is



(a) Willingness Wait 0.01 (b) Willingness Wait 0.8

Figure 6.2: Initial Function Time Curves



(a) Willingness 0.01

(b) Willingness 0.8

Figure 6.3: Initial Normalized Var Function Curves

also really high, the utility should be more than 0. The next function we tried was a polynomial function described by Equation 6.4. Z is a parameter that is used to scale. The values of Z we tried were 10 and 5.

$$U\_var = -\frac{1}{Z * willingness_{var}} * normalized_{var}{}^2 + 1 \tag{6.4}$$

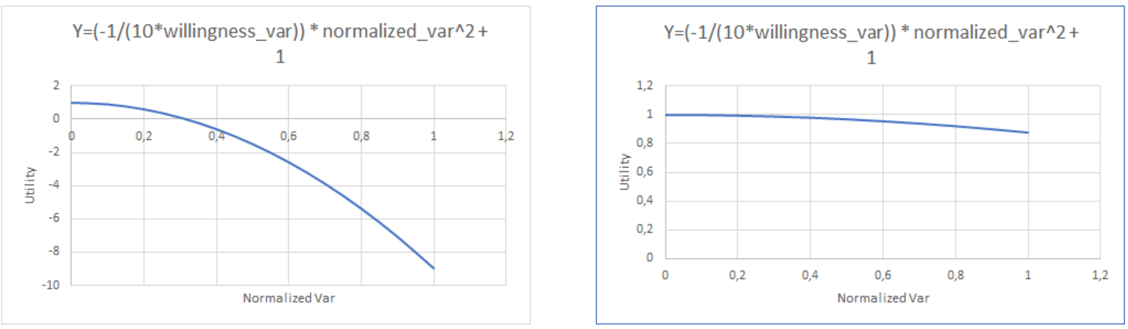
The graphs that describe Equation 6.4 are depicted in Figures 6.4 and 6.5.

We also decided to try different, simpler linear equations with the values of Z of 2 and 5. The equation is illustrated on 6.5.

$$U\_var = -\frac{1}{Z * willingness_{var}} * normalized_{var} + 1 \tag{6.5}$$

The graphs that describe Equation 6.5 are depicted in Figures 6.6 and 6.7.

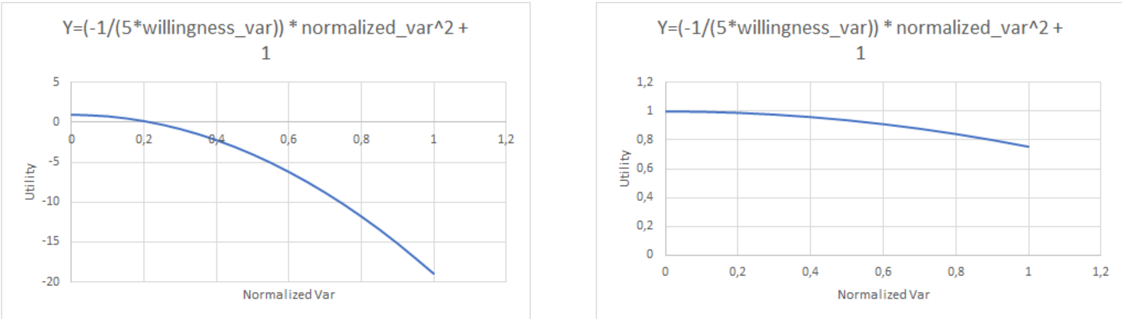
We ended up deciding that Equation 6.5 with Z=5, illustrated on Figure 6.7 would be the chosen equation. As illustrated in Figure 6.7, when the willingness variable has the minimum value of 0.01, worst case scenario the utility value is of -1. This shows the utility value for that service but does not give an unbalanced judgement to the service using only the cost and time utility. Even in a situation where the utility for one segment can be of -1, if that service is very



(a) Willingness 0.01

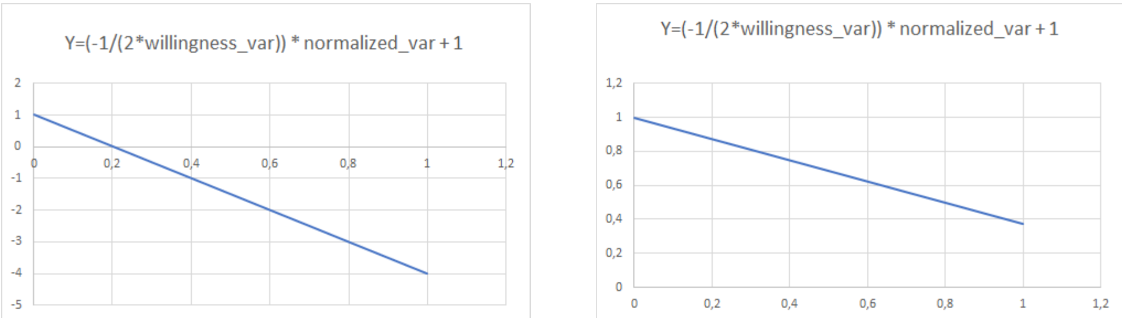
(b) Willingness 0.8

Figure 6.4: Polynomial Function Curves with Z=10



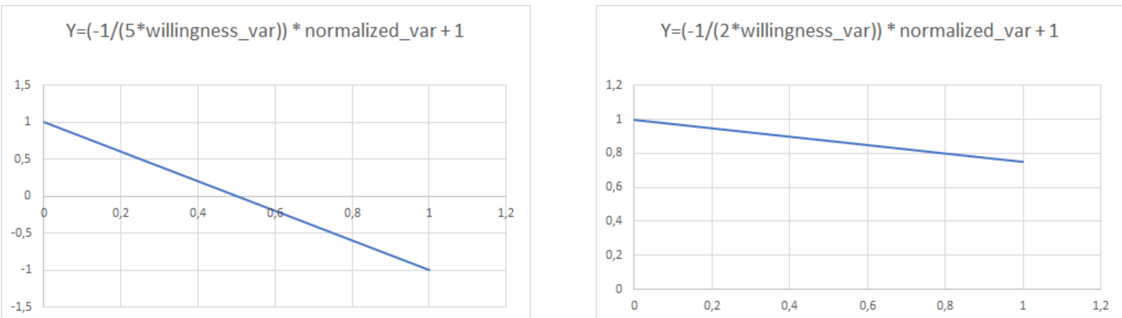
(a) Willingness 0.01 (b) Willingness 0.8

Figure 6.5: Polynomial Function Curves with Z=5



(a) Willingness 0.01 (b) Willingness 0.8

Figure 6.6: Linear Function Curves with Z=2



(a) Willingness 0.01 (b) Willingness 0.8

Figure 6.7: Linear Function Curves with Z=5

useful according to the other parameters, it can still end up with an overall positive utility. If we had a lower limit of example -8, even if the action had a good value according to the other parameters, it would still end up with a negative value.

6.3.2 Learning Technique Results

Now that we have an utility function, the next step was to experiment with different learning techniques. As stated before we tested our some learning methods which were more population or group based while also testing out more individual approaches. The main algorithms that were up for discussion were: Deep Q-Learning, Ensemble Learning and Weighted Average Experiences learning.

The approaches we have are:

1. Have a single neural net that would learn with the experiences of all the members of the population;

2. Have a single neural net for each agent that would learn with and dictate the service choice for that specific agent;

3. Have a neural net for each of the 5 clusters. Each neural net would learn with and choose the service only for agents belonging to that cluster;

4. Using ensemble learning, have 4 neural networks, each taking into consideration one of the segments of the utility function, that learn and decide for all the agents;

5. Use ensemble learning where each user has 4 learning agents, each taking into consideration one of the segments of the utility function, that vote in the service they deem better. These learning agents use neural nets to decide.

6. Use of ensemble learning, such as in method 5 but the difference is that the learner uses the weighted average of the past 200 experiences for each service.

7. For each agent, use the weighted average utility of the past 200 experiences for each available service to determine which service to choose;

We ultimately chose the technique that had better results, in regards to users picking the service that had a higher utility value for them and achieving a higher overall utility in the population, and also the technique that achieved better results in a timely manner.

In order to compare the methods we decided to pick a scenario, which ended up being scenario 4 since it was the one that had all the mobility services at the users disposal but that did not implement any of the incentive policies. We ran this simulation scenario 3 times, each of the runs would run for 3000 days, for each of the learning methods. To see if the number of users in the population made a big difference we tried with 100 users and with 800 users. Unfortunately some of the learning methods were estimated to take a great amount of time that we did not have so we do not have the utility values for those situations. Table 6.6 represents the average utility values for the different learning methods for both 100 and 800 users. Table 6.7 states the running time for a single 3000 days run, with each method.

Table 6.6: Average Total Utility per technique

Users	Techniques						
	1	2	3	4	5	6	7
100	2.327	2.454	2.152	2.018	NA	NA	2.47925
800	2.236	NA	2.244	2.294	NA	NA	2.394

[a] NA means Not Available since we were not able to get a value for the cell in a timely manner.

Table 6.7: Average Total Run time per learning method

Users	Techniques						
	1	2	3	4	5	6	7
Time 100 users (in hours)	0.42h	2.5h	0.33h	1h	26h+	~17h	0.17h
Time 800 users (in hours)	2h	230h+	2.5h	4h	NA	NA	~1.17h

[a] NA means Not Available since we were not able to get a value for the cell in a timely manner.

In Tables 6.6 and 6.7 some table cells have value NA. That happens because the learning methods take a long time for each of the runs, e.g. technique 5 would take approximately 17 hours just for one run with 3000 days.

Taking the results from Tables 6.6 and 6.7 in consideration, both the average utility and the time necessary for a single run, we ultimately decided on technique 7. Technique 7 has the highest average utility and takes an acceptable amount of time to produce results.

6.4 Simulation Results

Now that we have decided on the utility function and on the learning method, we can start implementing the different scenarios.

We decided to separate the performance measures, described in Section 3.6.2, into User performance measures and Organization performance measures. User performance measures for each of the scenarios is illustrated in Table 6.8 and Organization performance measures are described in Table 6.9. These performance measures are calculated using the average of the last 100 days with the exception of Quality of Service Time and Cost which only take into consideration the last day of the simulation.

Some table cells from Table 6.8 have symbols * and ** which were used to draw attention to these unusual values. In the cell with respect to Scenario 7- Quality of Service Cost- Ride Sharing, we have the value 0*. This means that nobody chose to use the ride sharing option in the last day.

Table 6.8: User Performance Measures

Original Variables	Scenarios							
	1	2	3	4	5	6	7	8
Average Travel Cost (in euros)								
Private Vehicle	3.976 €	3.577 €	NA	3.447€	4.473 €	13.652€	3.462 €	3.467 €
Public Transport	1.267 €	NA	1.350 €	1.378 €	1.380 €	1.357€	1.269 €	1.261 €
Ride Sharing	NA	NA	3.140 €	4.209 €	4.271 €	2.869 €	4.243 €	4.281 €
Total	2.621€	3.577 €	2.245€	3.011€	3.375 €	5.959 €	2.991 €	3.003€
Average Travel Time (in hours)								
Private Vehicle	0.221	0.199	NA	0.192	0.193	0.203	0.192	0.193
Public Transport	0.258	NA	0.271	0.274	0.274	0.272	0.273	0.273
Ride Sharing	NA	NA	0.266	0.347	0.358	0.251	0.361	0.354
Bicycle	0.083	NA	0.127	0.127	0.127	0.127	0.127	0.127
Walking	0.275	NA	0.244	0.244	0.242	0.241	0.242	0.243
Total	0.209	0.199	0.227	0.237	0.239	0.220	0.239	0.238
Quality of Service - Time								
Private Vehicle	~0	~0	NA	~0	~0	~0	~0	~0
Public Transport	-0.130	NA	-0.104	-0.096	-0.098	-0.110	-0.098	-0.097
Ride Sharing	NA	NA	-0.137	-0.079	-0.108	-0.203	0*	-0.147
Bicycle	-0.600	NA	-0.600	-0.600	-0.600	-0.600	-0.600	-0.600
Walking	-0.900	NA	-0.900	-0.900	-0.900	-0.900	-0.900	-0.900
Total	-4.07E-01	0	-0.435	-0.335	-0.341	-0.362	-0.399	-0.349
Quality of Service - Cost								
Private Vehicle	~0	~0	NA	~0	-0.353	-0.762	~0	~0
Public Transport	2.273	NA	2.273	2.273	2.273	2.273	50175711.8**	62310324.590 **
Ride Sharing	NA	NA	0.269	0.227	0.065	0.433	0*	0.263
Total	1.137	~0	1.271	0.833	0.662	0.648	25087855.9**	20770108.284**
Average Utility								
Private Vehicle	1.115	1.365	NA	2.130	2.082	1.590	2.128	2.134
Public Transport	2.168	NA	2.147	2.133	2.137	2.144	2.156	2.158
Ride Sharing	NA	NA	1.627	1.117	1.335	1.793	1.324	1.411
Bicycle	2.535	NA	2.553	2.597	2.585	2.576	2.597	2.596
Walking	2.261	NA	2.695	2.711	2.703	2.699	2.709	2.702
Total	2.020	1.365	2.255	2.138	2.168	2.160	2.183	2.200

[a] NA means Not Available since we were not able to get a value for the cell in a timely manner.

In another cell also related to Scenario 7 - Quality of Service Cost - Public Transport, we have a very high number, especially when compared to the values in other scenarios, followed by the symbol **. This is used to call to the attention that the value is so high because some members of the organization that used the public transport service redeemed their credits and were able to get their trip for free.

We should note that Quality of Service Time is approximately 0 for Private Vehicle. Quality of Service Time compares travel time spent with the chosen service with travel time if the service chosen was Private Vehicle. In this case the service chosen by the user was also Private vehicle so the travel time is the same for both. Similarly, Quality of Service Cost compares travel cost in the service chosen with travel cost if the service chosen was private vehicle. We can apply the same logic in this situation as in the case of Quality of service Time. The difference is that, in this case, we are comparing to the cost of using private vehicle with free parking, so that is why, in the scenarios where there exists a parking fee, the quality of service cost is lower than 0.

Table 6.9: Organization Performance Measures

Original Variables	Scenarios							
	1	2	3	4	5	6	7	8
Average Total Travel Time (in hours)	0.261 - 0.192	0.199 - 0.192	0.250 - 0.193	0.241 - 0.194	0.241 -0.193	0.245-0.193	0.241 -0.194	0.241 -0.194
Max Carbon Footprint (gCO2)	557 123.519	1 104 911.062	442 525.511	542 227.852	546 358.688	535 095.177	539 034.016	538 871.011
Cost (in euros)								
Max Carbon Tax	100.282 €	198.884 €	79.655 €	97.601 €	98.345 €	96.317 €	97.026 €	96.997 €
Max Transport Subsidy	3 889.120 €	13 765.320	1 160.170 €	3 590.610 €	3 506.810 €	3 576.297 €	3 472.357 €	3 489.607 €

During the simulation scenarios, it's possible for users to not be matched to any of the mobility services and end up staying at home that day instead of travelling to the destination. Table 6.10 presents the number of average users that were not able to find a suitable service for them during the each of the scenarios.

Table 6.10: Average Users not matched during the experiences

Users	Scenarios							
	1	2	3	4	5	6	7	8
Average unmatched users	142.32	0	81.09	66.24	66.99	66.38	65.97	66.03

From Table 6.10 we can see that scenarios 4–8 lose an average of 66 to 67 users while in scenario 1 we have a loss of 142 users and in scenario 3 we have a loss of 81 users. In scenario 2, where every user has a private vehicle and uses it to travel, there are 0 unmatched users.

In order to better compare the organization performance measures, since the 800 users are not always matched and there are differences in the number of unmatched users throughout the different scenarios, we decided to build Table 6.11. Table 6.11, which represents the organization performance measures values for the full 800 users, was constructed by using the values of Table 6.9 and the unmatched users from Table 6.10.

Table 6.11: Organization Performance Measures Normalized to 800 users

Original Variables	Scenarios							
	1	2	3	4	5	6	7	8
Average Total Travel Time (in min)	0.26 - 0.19	0.20 - 0.19	0.250 - 0.193	0.241 - 0.194	0.241 -0.193	0.245 - 0.193	0.241 -0.194	0.241 -0.194
Max Carbon Footprint (gCO2)	677 701.28	1 104 911.07	492 439.90	591 180.74	596 295.80	583 511.725	587 476.60	587 349.12
Cost (in euros)								
Max Carbon Tax	121.98 €	198.88 €	88.64 €	106.41 €	107.33€	105.032	105.75 €	105.72 €
Max Transport Subsidy	4 730.76 €	13 765.32	1 291.03 €	3 914.77 €	3 827.33 €	3 899.888	3 784.42 €	3 803.54 €

Regarding the mobility services choices and their fluctuations between scenarios we have decided to use the bar chart in Figure 6.13 to better illustrate the differences between scenarios.

The first three scenarios are the ones we believe establish some bounds related to the organization performance measures. Scenario 2 represents the worst case for the environment and for the organization's wallet while scenario 3 presents the best case for the environment and, consequently, the organization's finances. What this means is that in scenario 2, since all the users use private vehicle to commute to the destination, the carbon footprint hits the highest value, since private vehicles are the most pollutant, which in turn makes it so that the company has to pay a higher carbon tax. Transport subsidy also hits his highest since for private vehicle its 0.36 € per km while for public transport its 0.11 € and ride sharing its either 0.144€ or 0.11 €.

While on the topic of organization performance measures, we will now compare scenarios 4 through 8 according to those measures. Scenario 4 is, what we considered, our realistic base scenario since it's the first scenario where agents used reinforcement learning technique to understand the most useful service for them and also the first scenario where they could choose between all the implemented mobility services. Scenarios 5–8 apply incentive policies on top the base scenario 4. While neither of those scenarios improve on the average travel time metric, Scenarios 6,7 and 8 improved on the carbon footprint, carbon tax and transport subsidy while scenario 5 improved only on the transport subsidy.

Moving to the user performance measures, looking at scenarios 4~8 we can see that a lot of the measures stay pretty much the same in those scenarios with small changes only in relation to the ride sharing service. Ride Sharing has a lot of limitations for matching members of the community with each other which makes it the most volatile and gives it the lowest use rate.

Changes in the Average Travel Cost metric reflect the incentive scenarios in place. Average Travel Cost is highest for private vehicle in scenario 6 by approximately 10 €, which is the added cost of parking that exists in this scenario but not in the others. Similarly in scenario 5 we can also see that the average travel cost for private vehicle goes up 1€ in comparison with scenario 4 for the exact same reason. Quality of service - Cost is the metric where we can see the most changes, namely in scenarios 7 and 8, because in these scenarios, since we are implementing discounts through travel credits, some users can get their travels completely free of charge, which results in a very high value. In scenarios 5 and 6 free travels for services other than bicycling and walking cannot occur.

Regarding the Average Utility metric we can see that there are some differences between scenarios, albeit small, with scenario 8 being the one with the highest average utility value. Overall, from the scenarios where no mobility service is off limits, we have a higher utility for the users in scenario 8, with scenarios 5, 6 and 7 following closely behind. Generally all the scenarios that implement incentive policies have a higher utility and show better results for the users and the organization than scenario 1, which is the scenario responsible for illustrating mobility choices at the time of the survey.

For each scenario, besides text files with information related to the run, we also gather multiple charts that summarize what happened during that run in terms of usage of the multiple mobility services and consequently the emissions produced from the commute of the members of the organization. We will now present the charts resulting from one of the runs of scenario 4.

In Figure 6.8 we can see the distribution of services used throughout the day. Notice that the volume of services follows the normal distribution that characterizes the start time chosen by the users.

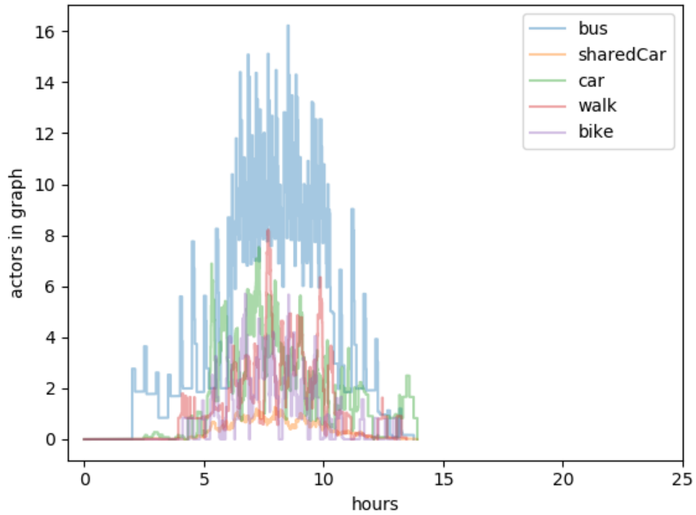


Figure 6.8: Actors distribution in Scenario 4

Figure 6.9 depicts the distribution of users for all the mobility services along the simulation. Bus, which is our public transport representative, is chosen by the majority of the users with second place being a tie between car (private vehicle) and bike/bicycle.

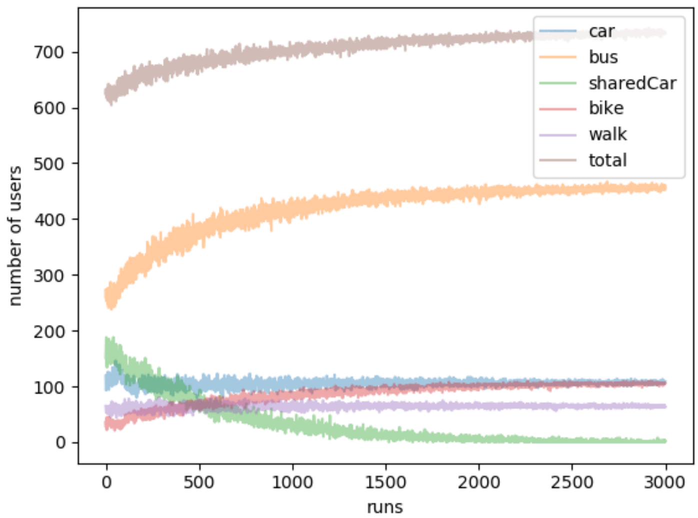


Figure 6.9: Users in Scenario 4

From Figures 6.10 and 6.11 we see the evolution of CO2 emissions throughout the experience. In Figure 6.10,notice that, even though the total bus emissions are higher than the total car emissions, that must not be confused with bus being worse for the environment than car but instead we are seeing approximately 460 agents using bus while only 100 agents use car. If we had the same number of users in both services, we would see that car emissions would be much higher. Figure 6.11 represents an average of the emissions each user releases throughout the scenario. Here we can see that, as discussed before, using a bus is indeed more environmentally conscious.

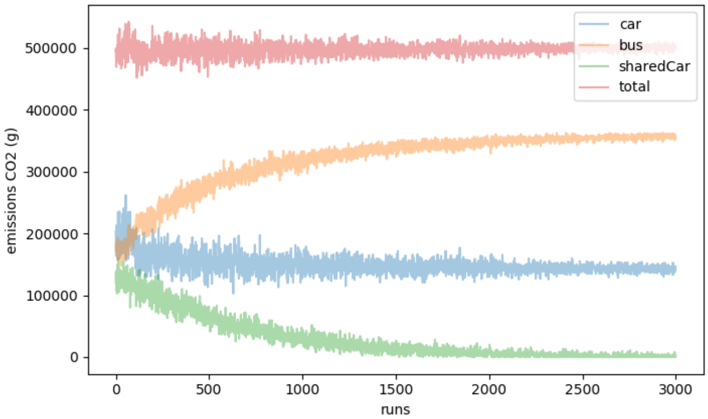


Figure 6.10: Emissions in Scenario 4

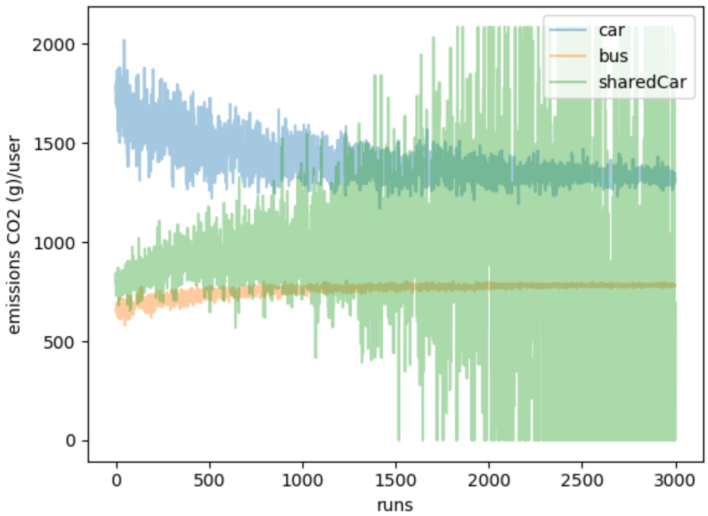


Figure 6.11: Emissions per user in Scenario 4

The final chart that is produced is depicted on Figure 6.12 and represents the evolution of the utility value for each of the services. We can see that the only service that behaves erratically is the Ride Sharing service (presented in the figure as Sharing). That happens since he is the only service that needs to match users with other users and that pairing can be tricky and change from day to day.

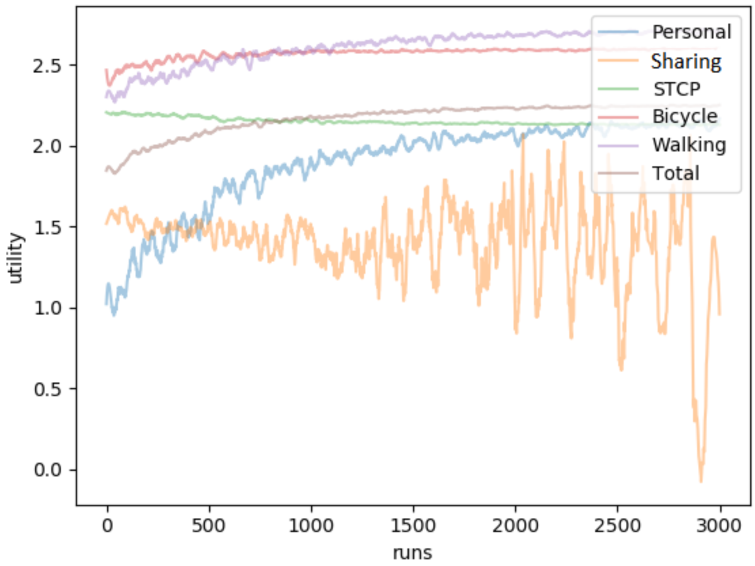


Figure 6.12: Utility in Scenario 4

6.4.1 Comparison between Scenarios Results

In order to better illustrate the differences between scenarios we created Figures 6.13, 6.14, 6.16,6.15,6.17, 6.18, 6.19, 6.20, 6.21.

Figure 6.13 represents the service ratio for the different scenarios. The first three scenarios serve to establish some bounds related to the organization performance measures. Scenario 1 uses the service distribution ratio directly from the surveyed. Ride Sharing was not considered one of the commuting options but private vehicle, bicycling, walking and public transport were all taken into consideration. In Scenario 2 all agents of society use their private vehicle to travel to the destination, this explains why in Figure 6.13, scenario 2 only shows car use. For Scenario 3 no agents have access to a private vehicle so they only have public transport, bicycling, walking and ride sharing at their disposal. These first three scenarios serve as a baseline for the current mobility situation (scenario 1) and to understand the upper (scenario 2) and lower (scenario 3) limits in terms of emissions and organization costs.

In scenario 4 the agents do not have restrictions about the services they can choose, they have all 5 mobility options at their disposal. It is also the first scenario where the agents have learning capability. Scenarios 5–8 implement different incentive policies. Scenarios 7 and 8 have similar service use ratios to scenario 4, while scenarios 5 and 6 have a higher public transport use and lower private vehicle use.

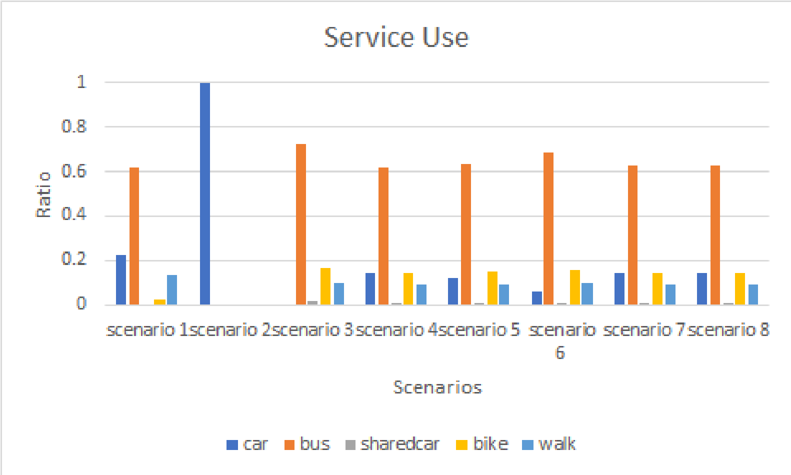


Figure 6.13: Service use ratio throughout all the simulation scenarios

From Figure 6.14 we can see that, besides scenario 2, the rest of the scenarios are very similar in regards to car use, with the lowest being scenario 6.

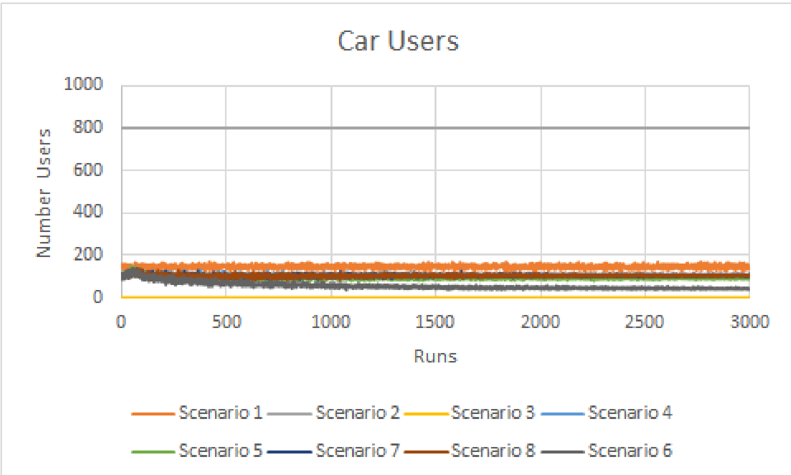


Figure 6.14: Car users throughout all the simulation scenarios

Figure 6.15 presents the Ride Sharing usage throughout the scenarios. Ride sharing is the trickier of the services and is almost never used. We can see that, in the beginning, we have a considerable amount of users that try the ride sharing service but that amount quickly decreases as time goes by.

Figure 6.16 illustrates the growth of the bus use across the scenarios. Scenario 3, which did not offer private vehicle as a mobility option, has the highest number of bus users followed closely by scenario 6, where we imposed a large parking fee to users who drived alone.

Bicycle user numbers, represented in Figure 6.17, are very stable throughout most of the scenarios. The same can be said for Walking users in Figure 6.18. The exception scenario in both

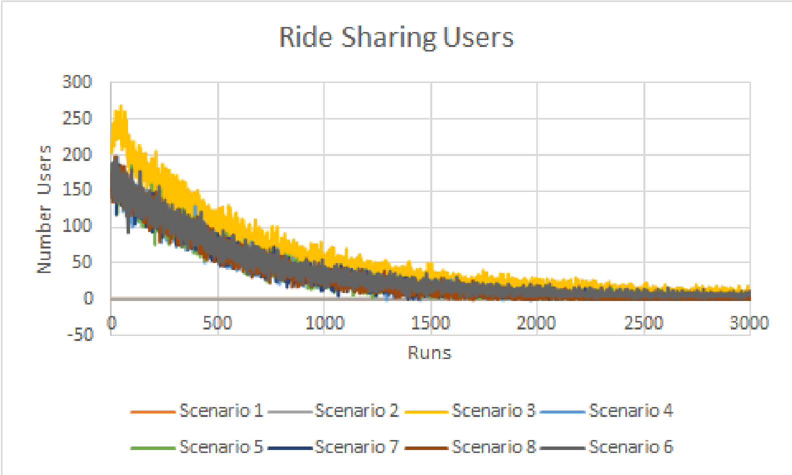


Figure 6.15: Ride Sharing users throughout all the simulation scenarios

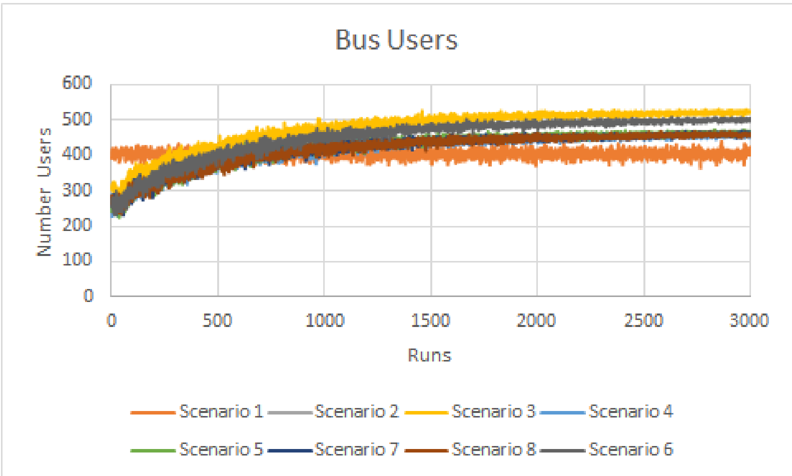


Figure 6.16: Bus users throughout all the simulation scenarios

those figures is scenario 1 because of the nature of the scenario, where the percentage of users for each transport mode is pre-defined..

When talking about total emissions, Figure 6.19,we can see a slight difference between each of the scenarios with scenario 2 having drastically higher emissions since it is the scenario where every single user only has their private vehicle at their disposal. Scenario 3 has the lowest emissions since private vehicle was not available.

In regards to Car and Bus emissions per user, illustrated in Figures 6.20 and 6.21 respectively, there are not any notable differences between scenarios.

Ride Sharing emissions per user, in Figure 6.22, is the most unstable out of the presented services because of the lack of users.

In summary, if we disregard the first three scenarios and only take into consideration scenario 4 as the base scenario and scenarios 5–8 which implemented incentive policies, we can say that

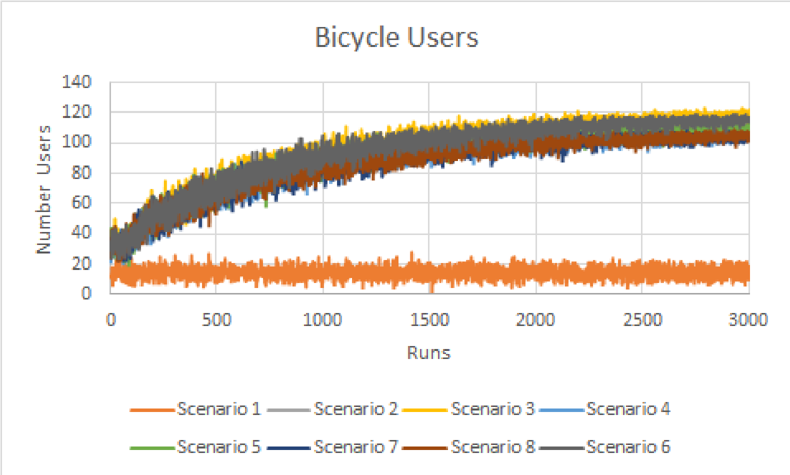


Figure 6.17: Bicycle users throughout all the simulation scenarios

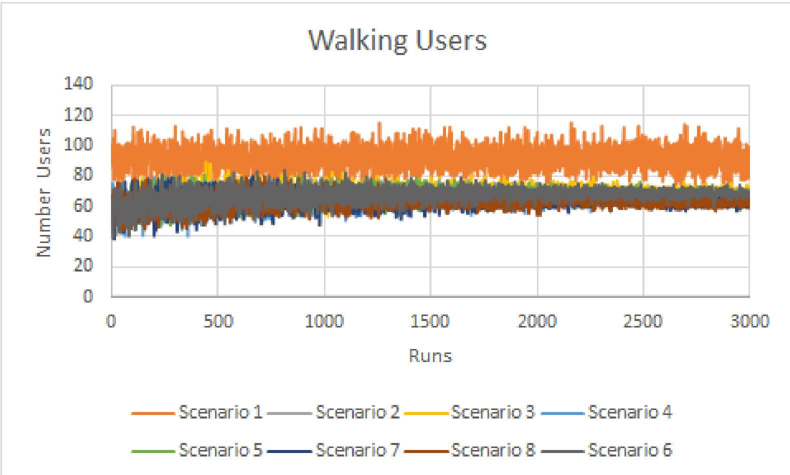


Figure 6.18: Walk users throughout all the simulation scenarios

the most notable differences in terms of service use are encountered in scenarios 5 and 6.

We will now take a closer look at scenarios 5 and 6, since they were the ones that achieved the most notable results, and compare differences between car usage with scenario 4.

6.4.2 Scenarios Comparison - User Analysis

Beyond the differences presented between the scenarios, we decided to dig a bit deeper and try to understand what kind of users were influenced by the incentive policies. Since we are studying how incentive policies influence the election of different mobility services we decided to compare the base scenario with all mobility services,scenario 4, with the scenarios that experienced most change in use percentage of mobility services,namely scenarios 5 and 6. While the ratio of the population members service use for all scenarios is illustrated on Figure 6.13, Table 6.12 takes

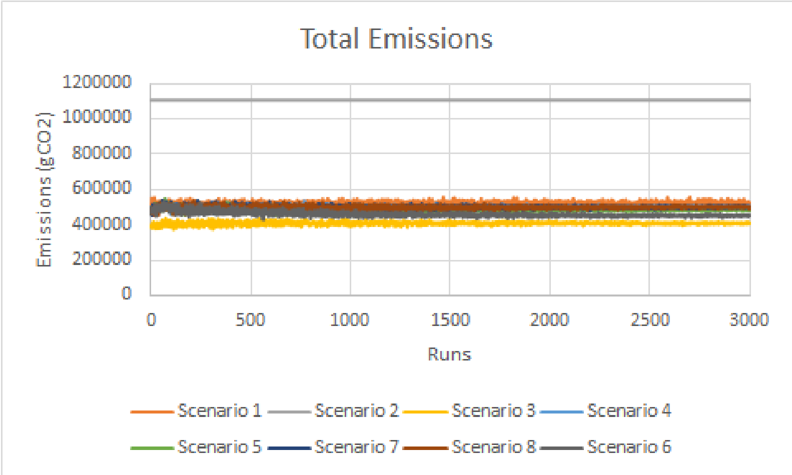


Figure 6.19: Total emissions throughout all the simulation scenarios

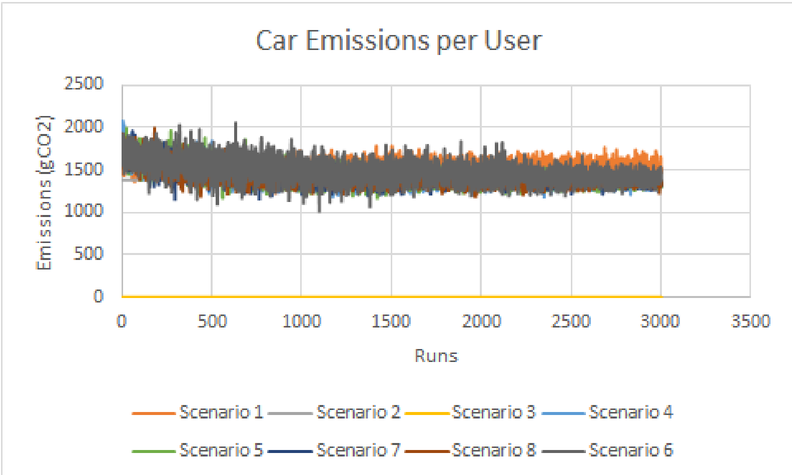


Figure 6.20: Car emissions per User throughout all the simulation scenarios

a closer look at the distribution of the population members between all the mobility services in simulation scenarios 4,5 and 6.

Table 6.12: Mobility Services Distribution

Services	Scenario 4	Scenario 5	Scenario 6
Private Vehicle	14.56%	12.32%	5.86%
Public Transport	62.11 %	63.30%	68.26 %
Ride Sharing	0.15%	0.15%	0.78 %
Bicycle	14.33%	14.97%	15.74%
Walking	8.85%	9.26%	9.38 %

We will first compare scenarios 4 and 5, since changes occurred in the services used in those scenarios, but the changes were not as notable as the changes between scenarios 4 and 6.

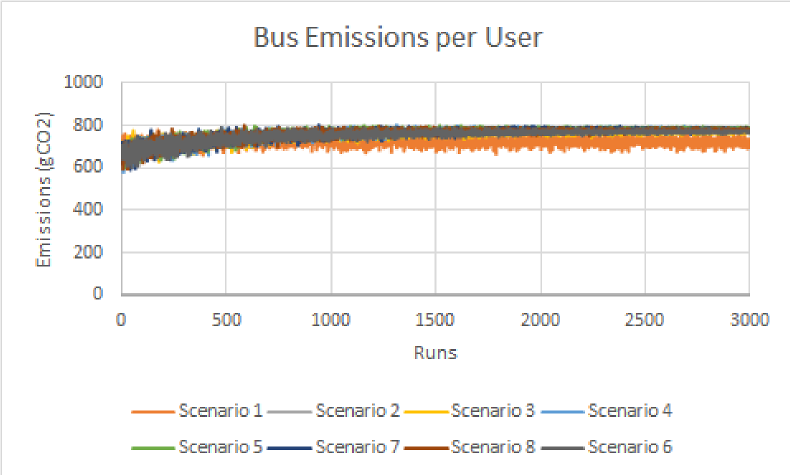


Figure 6.21: Bus emissions per User throughout all the simulation scenarios

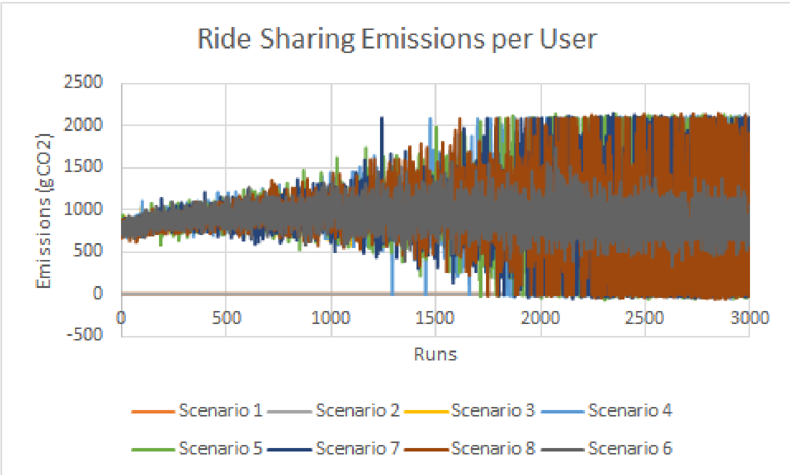


Figure 6.22: Ride Sharing per User throughout all the simulation scenarios

6.4.2.1 Scenarios 4 and 5

A total of 21 users changed from using Private Vehicle in scenario 4 to using Public Transport (10), Bicycle (6) and Walking(3). Two of those 21 users ended up not choosing any service. Meanwhile a total of 85 users that had used private transport continued using it, they were not affected by the incentive policy in place.

At first glance the affected users appear to not have any obvious characteristics as to why they decided to switch from private vehicle to other services. What we can see is that, of the 21 users, every user that had a bicycle and lived within bicycling distance chose to bicycle and if within walking distance and did not have a bicycle then they decided to walk. The remaining users decided to use public transport.

Since at first we did not find any obvious characteristics we decided to build a Decision Tree that would analyze the users characteristics and observe which of them influence the decision to switch from private vehicle to another mode. The resulting decision tree is illustrated on Figure 6.23.

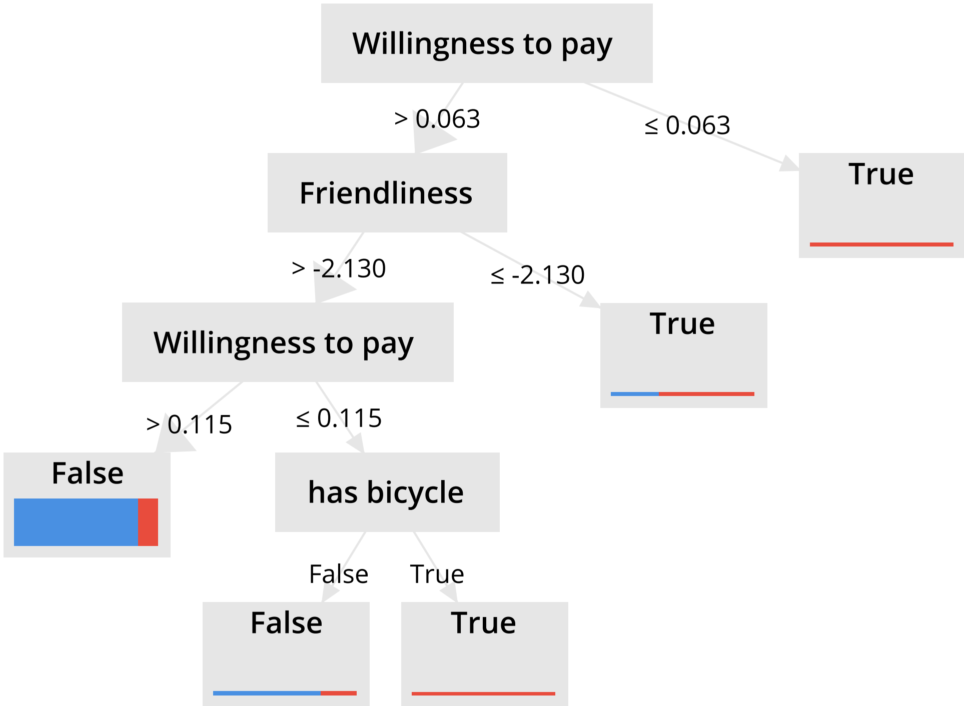


Figure 6.23: Decision Tree changes private vehicle users

We can see that the variables used to discern between users changing from private vehicle or not are willingness to pay, friendliness and if the user owns a bicycle. Willingness to pay is a very important variable since it defines the users relationship with travelling expenses and is directly part of the utility function. Most of our examples of users that did not switch from private transport, 81 out of the 85, have willingness to pay higher than 0.115 and friendliness factor higher than -2.130. When the willingness to pay is less than 0.063 the user switched from using private vehicle as the way to travel.

6.4.2.2 Scenarios 4 and 6

A total of 66 users changed from using Private Vehicle in scenario 4 to Public Transport (45), Bicycling(11), Walking(4) and even Ride Sharing(2) in scenario 6. Four of the 66 users ended up not choosing any service. Meanwhile a total of 45 users that had used private transport continued using it as they were not affected by the incentive policy in place. The number of switchers is three times as many as the ones from scenario 4 to scenario 5, which accounts for the bigger usage difference we can see on Table 6.12. Since there were a lot of users,we decided to again use Decision Tree to get a better understanding of the variables that played a part in the change between services. Figure 6.24 illustrates the resulting decision tree.

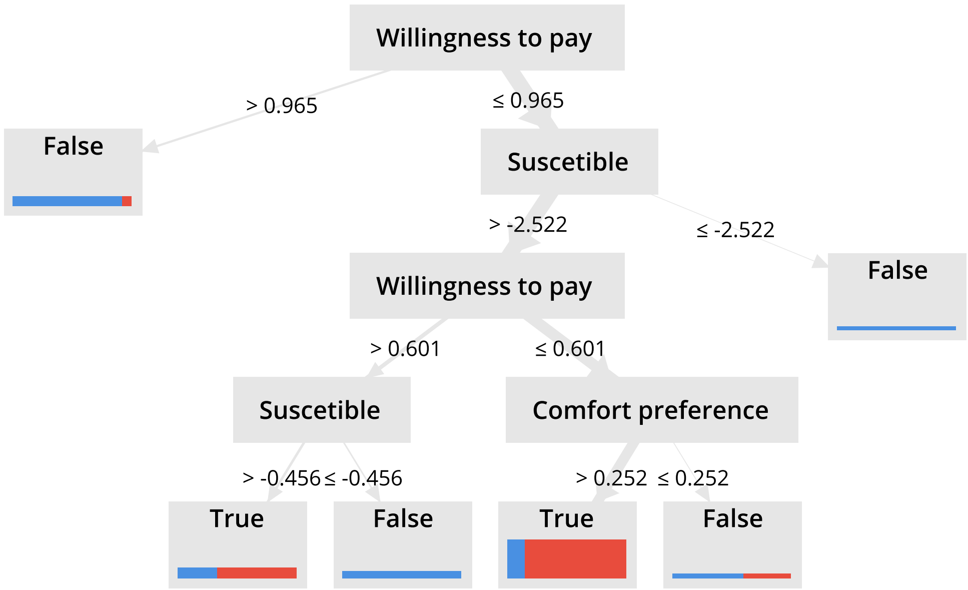


Figure 6.24: Decision Tree changes private vehicle users

We can see that in this case the most notable variables are still willingness to pay but we now have the factor susceptible and comfort preference. Most of the switchers are users with an average willingness to pay (less than 0.601) and with comfort preference higher than 0.252. Comfort preference, along with willingness to pay, is a parameter that appears directly in the utility function. Comfort preference indicates how much importance does the user give to the comfort of is trip. This is unexpected since comfort value is the highest for private vehicle, so we were anticipating that users with a higher comfort preference would remain using their private vehicle.

6.5 Chapter Summary

In this chapter we presented the experimental design used for the proof of concept, presented in Chapter 5, for the proposed meta-model and methodology planned on Chapter 3.

We created a total of 8 main simulation scenarios, designed to observe how different incentive policies influenced the use of mobility services. We were able to see how the incentive policies influenced the use of mobility services and how the users were able to adapt to the new circumstances and choose the better service for each of them. The incentive policy that achieved the better results overall was the one implemented on Scenario 6, where we applied a 10€ parking fee from solo trips.

Chapter 7

Conclusions

In this final chapter we recall the main concepts from the literature review and our work, while also addressing the methodology used, the experiments that were carried out, and the main insights gained into the experimental results. Lastly, we also discuss the main contributions of this study and propose possible directions to further this research in future work.

7.1 Main Contributions

We started our work by reviewing the areas of interest for this study and analyzing the main concepts of MaaS and Artificial Societies.

MaaS is a relatively new mobility concept which aims to integrate various forms of transport related services into a single platform, accessible on demand, capable of taking care of the user's individual travel needs. MaaS has the potential to become a solution for urban areas suffering from high congestion and poor traffic conditions. Artificial Societies are a useful metaphor to simulate real societies and the intricacies and interactions between agents. They consist of a collection of agents that interact with each other in a shared environment, possibly following some norms or rules. We used this concept in our work to study mobility choices.

After studying the main concepts we produced a gap analysis, presented at the end of the literature review chapter in Table 2.3, in which we were able to identify a gap in the current literature related to the topic of this study. Therefore, as for the main contributions of our work we proposed a meta-model to represent the mobility domain of closed communities, the players involved, and the interactions between them. We also reworked on an existing simulator and were able to thus create a simulation environment where we could implement our simulation scenarios for closed communities. We developed a simulation model where we instantiated the proposed meta-model in this work. That model used an artificial society created based on real data.

We are going to summarize each of the contributions. Starting with the meta-model,we adapted the work from Gomes [Gomes, 2019], which proposed a meta model that described the structure and dynamics of the MaaS concept in a multi-agent system, for the specific needs of our work. Our work focuses on closed communities while his work did not. We created a class diagram to better explain the intricacies and the intermediaries regarding the mobility market in closed communities.

In order to implement the model that characterized the closed communities we had to have a simulation environment. For that we decided to adapt the already existent meso-simulator HERMES [Cruz et al., 2019] for our specific needs. That included a lot of changes namely the introduction of multiple new concepts such as Users, Mobility Operators and Transportation services, the creation of a JSON setup file, import and save function for the agent population, the implementation of several utility functions and of multiple reinforcement learning methods etc.

The creation of the JSON file was a very important step since it allowed us to make quick changes and have a lot of the necessary information that characterized our population in a single file. The file has graph information, users information and mobility services information such as routes. We created a graph to represent a sort of city with paths that our agents could take to go to the destination. That graph had, for every edge, information about the volume, capacity and which transportation services could cross it.

The utility function is a fundamental part of the learning process. It gives us a numerical value of how much each action is worth, according to some characteristics. Finding a utility function which we considered acceptable was a lengthy process since we had to figure out the elements that we believe influence which mobility service is of better value for the user and we also had to decide on the function shape for each of those elements. We experimented with polynomial and linear functions with different scale values before deciding on the function shape for each of the elements.

Regarding the learning algorithms, we had to experiment with multiple different algorithms to finally figure out which presented the best results in a timely manner. The main algorithms we experimented with were Deep Q-learning, Ensemble Learning and the final one was Weighted Averages experiences. These algorithms are all based on the Reinforcement Learning umbrella where agents are expected to learn something receiving only numerical rewards to guide it through the learning process. This means the agents must learn how to map situations and actions in order to maximize a numerical reward signal.

In Deep Q-learning the agents use a neural network to map situations and actions to a reward value, according to an utility function. The neural network receives as input multiple pieces of information about the user and returns the expected reward values for all the possible actions, which in our case are the multiple transportation services. In Ensemble Learning, what was a single-objective reinforcement learning problem transformed into a multi-objective problem. We decided to have the same learning algorithm (Deep Q-learning) but have different learners for different segments of the reward signal. The final learning algorithm we implemented was Weighted Averages experiences. This technique is different from the others since, instead of having a neural network, it consists of saving the reward signal from the last experiences the user had with each of the possible actions. It then uses the weighted average of these experiences to decide on the mobility service. We thought about this technique since, given that every user would have a learner agent that implemented this method, and the user only has this one decision to make, the state information stays the same. This technique ended up being the one we chose to be used in our simulations since, while it was very simple, it was also the one that performed the best in terms of both results and running time.

For the creation of our agent society we used real data from a survey sent out to FEUP students. The data collected had to consequently be analyzed in order to extract useful information to characterize our users. Consequently the population created is a new society that was built from the survey sample, instead of it being completely synthetic with no values based on reality. This new population also had information, such as the transport emissions, that wasn't on the survey but that is based on other external sources.

We conducted several experiments and were able to see how the members of the society were affected by different incentive policies. Such incentive policies where comprised of monetary policies such as adding a parking fee or implementing a credit system where agents could trade credits for discounts. Adding a substantial parking fee was the incentive policy that produced the most change.

7.2 Limitations

During the course of this work and as we made progress in the development of our methodology, we were able to identify limitations of our approach, discussed further as follows.

The survey used to collect data was not designed specifically with this work in mind and because of that some data that would be interesting to have,such as knowing more specifically how effective incentives could be, and what type of incentives would be more motivating.

More questions related to money spent and how willing would people be to spend money according to different advantages and disadvantages. Another factor that possibly limited the results we achieved was the utility function. It is difficult to model into a function the reasoning behind people's cognitive processes and what would drive them to select a mobility service.

Finally, running each of the multiple scenarios was a very time-consuming task. This prevented us from exploring more incentive policies, as well as other factors such as exploring relations between users and how they affect the mobility choices.

7.3 Future Work

As future work, we consider that there are some changes that could be done to improve the performance of this work.

The user cannot chain multiple services to reach the destination. For example, the user cannot choose to walk to another node where he could then get onto a bus to go to the destination. This would be interesting to study further, so as to allow for more MaaS options and respective benefits to be explored.

We did not have the opportunity to explore further some extra and more advanced learning methods because of the long running time associated with their processes. It would be thus interesting to evaluate whether implementing the simulator in another language, such as Java for instance, would be beneficial to save simulation time.

It would be equally appropriate to add more services such as charging stations for electric vehicles, and also add extra incentives for the ride sharing service. This would allow us to see how such alternative strategies influence matches, for instance. We also needed to explore how realistic truly are our results and if they could be applied to the real world.

Another point that could be improved is the utility function, since it dictates what the agent learns. The utility function could be more realistic thus enriching the representational ability of our model. However, inferring or devising such a function is a difficult and nontrivial task that will require further exploration into multidisciplinary fields.

Appendix A

Survey

Ride Sharing na FEUP

Este inquérito insere-se no âmbito da Unidade Curricular de Modelação e Simulação de Sistemas (MSSI) do 4º ano do MIEIC e tem como intuito descobrir a nossa pegada ecológica (comunidade FEUP) , tendo em conta as viagens diárias que todos nós fazemos para nos deslocarmos para a FEUP.

Com os dados obtidos, esperamos ter uma melhor ideia de como ride sharing poderia diminuir o impacto que temos no ambiente e na nossa carteira como resultado do nosso estilo de viagens! :)

Este inquérito é completamente anónimo e será conduzido de acordo com as regras GDPR de proteção de dados (eugdpr.org).

Considerem o trajeto desde a vossa residência até à FEUP e/ou da FEUP até à residência, em tempos escolares.
Nas perguntas que se seguem, apenas são consideradas viagens em um sentido. Portanto, o percurso casa-FEUP-casa implicará duas viagens. Paragens intermédias são desconsideradas.

No fim do inquérito podes ficar habilitado a 1 dos 3 copos de café em bambu da loja da FEUP que temos para oferecer!(https://paginas.fe.up.pt/~loja/index.php?route=product/product&path=67_69&product_id=173)

*Obrigatório

Dados Demográficos

Idade: *

- 17 - 20
- 21 - 24
- 25 - 28
- 29+

Género: *

- Feminino
- Masculino
- Prefiro não responder

Tens carta de condução? *

- Sim
- Não

Se sim, há quantos anos tiraste a carta?

- 0 - 1
- 2 - 3
- 4 - 5
- 6 - 7
- 8+

Tens transporte privado que podes usar para te deslocar para a FEUP? *

- Sim
- Não

Detalhes do veículo

Tens: *

- Carro
- Mota
- Bicicleta

◯ Outra: ____________

O teu veículo é: *

◯ A gasolina
◯ A gasóleo
◯ Hibrído
◯ Elétrico
◯ Outra: ____________

O teu veículo tem quantos lugares disponíveis habitualmente? *

◯ 0
◯ 1
◯ 4
◯ Outra: ____________

Se souberes, quanto é o consumo aproximado da tua viatura (em litros de combustível/100Km)?

A sua resposta

Estilo de Viagem

Para te deslocares até à faculdade, utilizas transporte privado ou transporte público? *

◯ Transporte Privado
◯ Transporte Público
◯ A pé/bicicleta
◯ Transporte Público e Privado

Aproximadamente, quantos km é o teu trajeto até à faculdade? *

Se não sabes podes estimar usando o Google Maps com destino na FEUP: www.google.com/maps/dir//41.1775593,-8.5979258. (Não temos acesso aos dados introduzidos no Google Maps)

A sua resposta

Vives dentro ou fora do Porto (Concelho do Porto), durante o tempo escolar? *

◯ Dentro
◯ Fora

Aproximadamente, quanto dinheiro gastas em combustível por mês? *

◯ 0€
◯ 0€ a 20€
◯ 20€ a 40€
◯ 40€ a 60€
◯ 60€ a 80€
◯ 80€ a 100€
◯ 100€ a 120€
◯ 120€ a 140€
◯ 140€ a 160€
◯ 160€+

- Não sei

Aproximadamente, quanto dinheiro gastas em Transportes Públicos por mês? *

- 0€
- 0€ a 15€
- 15€ a 30€
- 30€ a 45€
- 45€ a 60€
- 60€ a 75€
- 75€+
- Não sei

Quantas viagens fazes por semana, em média, para te deslocares para a FEUP e de volta? *

"percurso casa-FEUP-casa implicará duas viagens. Paragens intermédias são desconsideradas."

- 2 - 4
- 6 - 8
- 10 - 12
- 14 - 16
- 18 - 20
- 22+

Ride Sharing

Sabes o que é "Ride Sharing"? *

- Sim
- Não

Sobre ride sharing: *

Caso não saibas, de forma simplificada é "o uso partilhado de um automóvel particular por duas ou mais pessoas, para viajar juntos durante o percurso para o trabalho ou a escola. (...) contribuindo para a redução do congestionamento e diminuindo a poluição do ar"
pt.wikipedia.org/wiki/Carona_solid%C3%A1ria

- Utilizo
- Não utilizo

Estarias disposto(a) a utilizar ride sharing: *

	1	2	3	4	5	
Não/Nunca	○	○	○	○	○	Sim/Sempre

Partilhavas a tua viagem para a FEUP com: *

	1 (Não/Nunca)	2	3	4	5 (Sim/Sempre)
Amigos	○	○	○	○	○
Colegas do teu ano	○	○	○	○	○
Colegas do teu curso	○	○	○	○	○
Outros estudantes da FEUP	○	○	○	○	○

Incentivos

Abaixo temos algumas ideias para incentivar a pratica de ride sharing pelos alunos da FEUP.
Classifica cada uma delas de acordo com o quão te incentivariam a praticar ride sharing.

Se ainda não é um hábito teu praticar ride sharing, o que te incentivaria?

	1 (Não interessado)	2	3	4	5 (Muito interessado)
Crédito para o sistema de impressões	○	○	○	○	○
Crédito para as máquinas de café	○	○	○	○	○
Crédito na cantina	○	○	○	○	○
Crédito na loja FEUP (fe.up.pt/loja)	○	○	○	○	○
Desconto nas propinas	○	○	○	○	○
Estacionamento Prioritário para quem oferece boleia	○	○	○	○	○

Que outros incentivos achas que seriam interessantes?

A sua resposta

Sorteio

Se quiseres participar no sorteio dos copos reutilizáveis, introduz aqui o teu email e boa sorte! :)

A sua resposta

Appendix B

Factor Loadings

Table B.1: Factor Loadings

Original Variables	Factors				
	Friendliness	Suscetible	Transport	Urban	Willing
Carta de conducao	-0.009	-0.072	0.367	0.066	0.018
Transporte privado	-0.025	-0.166	0.796	0.096	0.065
Deslocacao trajeto	0.005	0.035	-0.508	-0.181	0.157
Distancia trajeto	0.051	0.026	0.154	0.911	0.054
Viver dentro ou fora	-0.030	-0.062	0.126	0.629	-0.036
Dinheiro Combustivel	0.049	-0.107	0.688	0.207	0.008
Dinheiro Transportes Publicos	0.002	0.052	-0.503	0.374	0.046
Numero Viagens	0.080	0.047	-0.057	-0.190	0.007
Utilizar ride sharing	0.040	-0.023	-0.038	-0.001	0.643
Disposto a utilizar ride sharing	0.499	0.172	0.041	0.018	0.328
Viagem com Amigos	0.577	0.141	0.009	-0.037	-0.003
Viagem com Colegas do teu ano	0.890	0.116	-0.013	-0.087	0.016
Viagem com Colegas do teu curso	0.918	0.147	0.016	-0.041	0.018
Viagem com Outros estudantes da FEUP	0.762	0.133	-0.016	-0.048	-0.027
Incentivo Credito para o sistema de impressoes	0.115	0.565	-0.132	0.025	0.001
Incentivo Credito para as maquinas de café	0.070	0.630	-0.020	-0.088	-0.046
Incentivo Credito na cantina	0.092	0.650	-0.135	-0.041	-0.029
Incentivo Credito na loja FEUP	0.106	0.593	-0.182	-0.074	0.154
Incentivo Desconto nas propinas	0.128	0.484	-0.051	-0.022	-0.041
Incentivo Estacionamento Prioritario para quem oferece boleia	0.202	0.353	0.270	0.038	0.087

Appendix C

Configuration JSON File

This configuration file has information about the graph as well as the population. Structure:

- graph information: number of nodes,start node,end node,edges information such as the services allowed to traverse it
- users information:number of users,number of clusters, friends distribution,salary distribution, has bicycle ratio,clusters distribution
- Distribution about information related to each of the clusters: factors, distance, seats, has private vehicle ratio
- Courses information, punishment when picking a service impossible to have e.g. a person that doesn't own a private vehicle, choosing to travel using a private vehicle and utility value for unviable choice e.g. when a user chooses ride sharing but isn't matched up and therefore can't make the trip
- Bus routes

```json
{
    "graph": {
        "num_nodes": 97,
        "start_node": 0,
        "end_node": 24,
        "edges_list": {
            "0,1": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
```

```
            },
            "0,7": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "1,2": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "1,8": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "2,3": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "2,9": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
```

```
                    "bike"
                ]
            },
            "4,3": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "3,10": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "5,4": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "4,11": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "6,5": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
```

```
                "sharedCar",
                "car",
                "bus"
            ]
        },
        "5,12": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "6,13": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus"
            ]
        },
        "7,8": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "7,14": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "8,9": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
```

```
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "8,15": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "9,10": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "9,16": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "11,10": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "10,17": {
                "color": "red",
```

```
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "12,11": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "11,18": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "13,12": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "12,19": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
```

```
                ]
            },
            "13,20": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "14,15": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "14,21": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "15,16": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "15,22": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
```

```
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "16,17": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "16,23": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "18,17": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "17,24": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
```

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            "19,18": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "18,25": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "20,19": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "19,26": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "20,27": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
```

```
                    "bus",
                    "bike"
                ]
            },
            "21,22": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "28,21": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "22,23": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "29,22": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "23,24": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
```

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                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "30,23": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "25,24": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "31,24": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "26,25": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
```

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                    "bike",
                    "walk"
                ]
            },
            "32,25": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "27,26": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "33,26": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "34,27": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "28,29": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
```

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                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "35,28": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "29,30": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "36,29": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "30,31": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
```

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            "37,30": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "32,31": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "38,31": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike",
                    "walk"
                ]
            },
            "33,32": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "39,32": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
```

```
                "car",
                "bus",
                "bike"
            ]
        },
        "34,33": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "40,33": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "41,34": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "35,36": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
            "capacity": 50,
            "allowed_transports": [
                "sharedCar",
                "car",
                "bus",
                "bike"
            ]
        },
        "42,35": {
            "color": "red",
            "volume": 0,
            "free_flow_travel_time": 1,
```

```
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "36,37": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "43,36": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "37,38": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "44,37": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "39,38": {
                "color": "red",
```

```
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "45,38": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "40,39": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "46,39": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "41,40": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
```

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            },
            "47,40": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "48,41": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "42,43": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "49,42": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "43,44": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
```

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            },
            "44,45": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "46,45": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "47,46": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus",
                    "bike"
                ]
            },
            "48,47": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "50,49": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
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                ]
            },
            "51,50": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "52,51": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "53,52": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "54,53": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "55,54": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
```

```
            "56,55": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "57,56": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "58,57": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "59,58": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "60,59": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "61,60": {
                "color": "red",
```

```
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "62,61": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "63,62": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "64,63": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "65,64": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "66,65": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
```

```
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "67,66": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "68,67": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "69,68": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "70,69": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "71,70": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
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                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "72,71": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "73,6": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "74,73": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "75,74": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "76,75": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
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                        "bus"
                    ]
                },
                "77,76": {
                    "color": "red",
                    "volume": 0,
                    "free_flow_travel_time": 1,
                    "capacity": 50,
                    "allowed_transports": [
                        "sharedCar",
                        "car",
                        "bus"
                    ]
                },
                "78,77": {
                    "color": "red",
                    "volume": 0,
                    "free_flow_travel_time": 1,
                    "capacity": 50,
                    "allowed_transports": [
                        "sharedCar",
                        "car",
                        "bus"
                    ]
                },
                "79,78": {
                    "color": "red",
                    "volume": 0,
                    "free_flow_travel_time": 1,
                    "capacity": 50,
                    "allowed_transports": [
                        "sharedCar",
                        "car",
                        "bus"
                    ]
                },
                "80,79": {
                    "color": "red",
                    "volume": 0,
                    "free_flow_travel_time": 1,
                    "capacity": 50,
                    "allowed_transports": [
                        "sharedCar",
                        "car",
                        "bus"
                    ]
                },
                "81,80": {
                    "color": "red",
                    "volume": 0,
                    "free_flow_travel_time": 1,
                    "capacity": 50,
                    "allowed_transports": [
                        "sharedCar",
                        "car",
                        "bus"
                    ]
```

```
            },
            "82,81": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "83,82": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "84,83": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "85,84": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "86,85": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "87,86": {
```

```
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "88,87": {
                "color": "red",
                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
                    "sharedCar",
                    "car",
                    "bus"
                ]
            },
            "89,88": {
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                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
                "allowed_transports": [
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                    "car",
                    "bus"
                ]
            },
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                "volume": 0,
                "free_flow_travel_time": 1,
                "capacity": 50,
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                    "bus"
                ]
            },
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                "capacity": 50,
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                    "bus"
                ]
            },
            "92,91": {
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                "capacity": 50,
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                    "bus"
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                    "car",
                    "bus"
                ]
            },
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                "capacity": 50,
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                    "bus"
                ]
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                "free_flow_travel_time": 1,
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                    "bus"
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        "has_bike": 0.3,
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            "cluster_2": 0.494,
            "cluster_3": 0.842,
            "cluster_4": 1
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                    "stand_div": 5.327933218836145,
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                    "mean": -0.09679459183917238,
                    "stand_div": 2.1831710610864796,
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                    "max_value": 2.025
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                "has_private": {
                    "ratio": 0.993
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                    "1": 0.143,
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                    "3": 0.071,
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                    "6": 0.007
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                "original_choices": {
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                        "bus": 0,
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                    "1-3": {
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                        "bike": 0.1236,
                        "walk":0.2884
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                    "3-5": {
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                        "bus": 0.333,
                        "bike": 0.0501,
                        "walk":0.1169
                    },
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                        "bike": 0.009,
                        "walk":0.021
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                    "10-20": {
                        "car": 0.679,
                        "bus": 0.321,
                        "bike": 0,
                        "walk":0
                    },
                    "20-30": {
                        "car": 0.750,
                        "bus": 0.250,
                        "bike": 0,
                        "walk": 0
                    },
                    "30": {
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                        "bus": 0,
                        "bike": 0,
                        "walk":0
                    }
                }
            },
            "cluster_1": {
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                    "stand_div": 1.369692988221527,
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                    "stand_div": 4.7725331496201555,
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                "transport": {
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                    "stand_div": 0.64867688744728,
                    "shape": {
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                    "max_value": 1.822
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                    "max_value": 0.693
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                "has_private": {
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                "seat_probs": {
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                    "1": 0.216,
                    "2": 0.054,
                    "3": 0.108,
                    "4": 0.622,
                    "5": 0,
                    "6": 0
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                        "b": 4.495200630556196
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                    "min_value": 0.500,
                    "max_value": 32.000
                },
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                        "bus": 0,
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                        "bike": 0.3,
                        "walk": 0.7
                    },
                    "1-3": {
                        "car": 0.059,
                        "bus": 0.294,
                        "bike": 0.1941,
                        "walk":0.4529
                    },
                    "3-5": {
                        "car": 0.111,
                        "bus": 0.556,
                        "bike": 0.0999,
                        "walk":0.2331
                    },
                    "5-10": {
                        "car": 0.304,
                        "bus": 0.652,
                        "bike": 0.0129,
                        "walk":0.0301
                    },
                    "10-20": {
                        "car": 0.250,
                        "bus": 0.750,
                        "bike": 0,
                        "walk":0
                    },
                    "20-30": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    },
                    "30": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    }
                }
            },
            "cluster_2": {
                "friendliness": {
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                    "stand_div": 1.5946611829055584,
                    "shape": {
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                    "min_value": -1.659,
                    "max_value": 1.513
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                    "stand_div": 5.49096613378113,
                    "shape": {
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                        "a": 3.5762389507590147,
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                    "shape": {},
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                "seat_probs": {
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                    "1": 0.056,
                    "2": 0,
                    "3": 0.111,
                    "4": 0.722,
                    "5": 0.056,
                    "6": 0
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                    "max_value": 35.700
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                        "car": 0,
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                        "bike": 0.3,
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                    "1-3": {
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                        "bike": 0.15,
                        "walk":0.35
                    },
                    "3-5": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    },
                    "5-10": {
                        "car": 0.375,
                        "bus": 0.5,
                        "bike": 0.0375,
                        "walk":0.0875
                    },
                    "10-20": {
                        "car": 0.182,
                        "bus": 0.818,
                        "bike": 0,
                        "walk":0
                    },
                    "20-30": {
                        "car": 0.5,
                        "bus": 0.5,
                        "bike": 0,
                        "walk":0
                    },
                    "30": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    }
                }
            },
            "cluster_3": {
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                    "shape": {
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                    "max_value": 0.317
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                "urban": {
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                    "mean": -0.9556439644904786,
                    "stand_div": 0.25499417923674605,
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                    "shape": {
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                    "max_value": 0.498
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                "has_private": {
                    "ratio": 0.016
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                "seat_probs": {
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                    "1": 0.250,
                    "2": 0,
                    "3": 0.250,
                    "4": 0.125,
                    "5": 0,
                    "6": 0
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                "distance": {
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                    "mean": 0.39999999999999997,
                    "stand_div": 4.484355333431133,
                    "shape": {
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                    },
                    "min_value": 0.400,
                    "max_value": 22.000
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                    "1-3": {
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                        "bus": 0.298,
                        "bike": 0.2106,
                        "walk":0.4914
                    },
                    "3-5": {
                        "car": 0,
                        "bus": 0.952,
                        "bike": 0.0144,
                        "walk":0.0336
                    },
                    "5-10": {
                        "car": 0.028,
                        "bus": 0.972,
                        "bike": 0,
                        "walk":0
                    },
                    "10-20": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    },
                    "20-30": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    },
                    "30": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk":0
                    }
                }
            },
            "cluster_4": {
                "friendliness": {
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                    "mean": 0.7383501903264711,
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                    "max_value": 1.521
                },
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                        "max_value": 1.733
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                        "mean": -1.4852104128484742,
                        "stand_div": 1.6604595030660974,
                        "shape": {
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                        "min_value": -1.457,
                        "max_value": 1.940
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                    "urban": {
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                        "stand_div": 1.355236086760907,
                        "shape": {
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                        },
                        "min_value": 0.609,
                        "max_value": 3.927
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                    "willing": {
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                        "stand_div": 1.4182744495807915,
                        "shape": {
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                        "max_value": 2.185
                    },
                    "has_private": {
                        "ratio": 0.506
                    },
                    "seat_probs": {
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                        "2": 0.071,
                        "3": 0.024,
                        "4": 0.786,
                        "5": 0,
                        "6": 0
                    },
                    "distance": {
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                        "mean": 33.41130267780011,
                        "stand_div": 5.083316072702319,
                        "shape": {},
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                        "bike": 0,
                        "walk":0
                    },
                    "1-3": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk": 0
                    },
                    "3-5": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk": 0
                    },
                    "5-10": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk": 0
                    },
                    "10-20": {
                        "car": 0,
                        "bus": 1,
                        "bike": 0,
                        "walk": 0
                    },
                    "20-30": {
                        "car": 0.105,
                        "bus": 0.895,
                        "bike": 0,
                        "walk": 0
                    },
                    "30": {
                        "car": 0.302,
                        "bus": 0.698,
                        "bike": 0,
                        "walk": 0
                    }
                }
            }
        },
        "num_courses": 9,
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            "course_1": 0.219,
            "course_2": 0.254,
            "course_3": 0.338,
            "course_4": 0.554,
            "course_5": 0.711,
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            "course_7": 0.928,
            "course_8": 1
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                "year_1": 0.377,
                "year_2": 0.565,
                "year_3": 0.773,
                "year_4": 1
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            "course_1": {
                "year_0": 0.208,
                "year_1": 0.406,
                "year_2": 0.590,
                "year_3": 0.779,
                "year_4": 1
            },
            "course_2": {
                "year_0": 0.218,
                "year_1": 0.388,
                "year_2": 0.543,
                "year_3": 0.697,
                "year_4": 1
            },
            "course_3": {
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                "year_1": 0.380,
                "year_2": 0.591,
                "year_3": 0.782,
                "year_4": 1
            },
            "course_4": {
                "year_0": 0.193,
                "year_1": 0.393,
                "year_2": 0.559,
                "year_3": 0.746,
                "year_4": 1
            },
            "course_5": {
                "year_0": 0.188,
                "year_1": 0.394,
                "year_2": 0.599,
                "year_3": 0.772,
                "year_4": 1
            },
            "course_6": {
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                "year_1": 0.353,
                "year_2": 0.545,
                "year_3": 0.730,
                "year_4": 1
            },
            "course_7": {
                "year_0": 0.178,
                "year_1": 0.397,
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                "year_2": 0.575,
                "year_3": 0.788,
                "year_4": 1
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            "course_8": {
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                "year_1": 0.377,
                "year_2": 0.546,
                "year_3": 0.749,
                "year_4": 1
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        },
        "personality_params": {
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                "stand_div": 0.3
            },
            "awareness": {
                "mean": 0.5,
                "stand_div": 0.3
            },
            "comfort_preference": {
                "mean": 0.5,
                "stand_div": 0.3
            }
        },
        "punishment_doesnt_have_mode": -100,
        "unviable_choice": -2
    },
    "buses": {
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            1,
            2,
            3,
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            17,
            24
        ],
        "route_1": [
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            8,
            9,
            10,
            17,
            24
        ],
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            15,
            16,
            17,
            24
        ],
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            24
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            43,
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            29,
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            23,
            24
        ],
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            46,
            45,
            38,
            31,
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            24
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            24
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        ],
        "route_9": [
            96,
            95,
            94,
            93,
            92,
            91,
            90,
            89,
            88,
            87,
            86,
            85,
            84,
            83,
            82,
            81,
            80,
            79,
            78,
            77,
            76,
            75,
            74,
            73,
            6,
            13,
            20,
            27,
            26,
            25,
            24
        ],
        "route_10": [
            76,
            75,
            74,
            73,
            6,
            5,
```

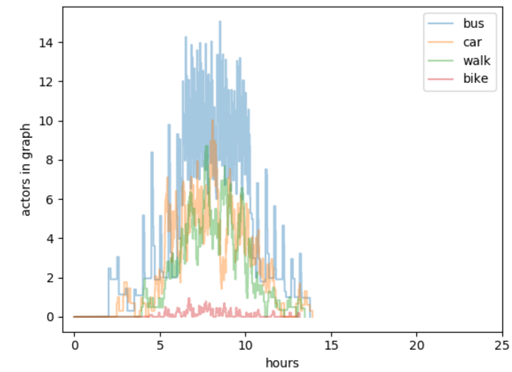
```
            12,
            19,
            26,
            25,
            24
        ],
        "route_11": [
            4,
            11,
            18,
            25,
            24
        ]
    }
}
```

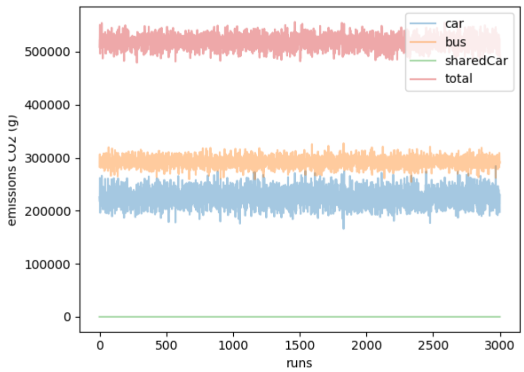
Appendix D

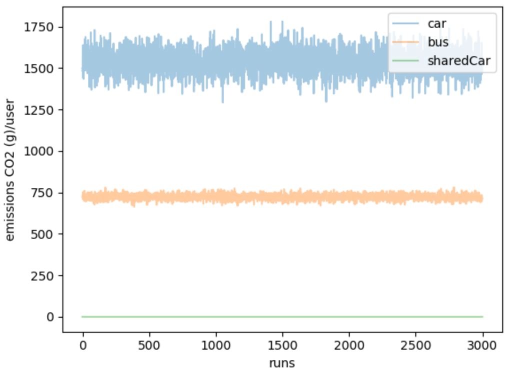
Simulation Results

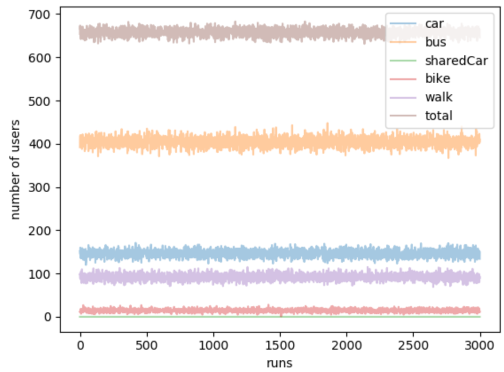
D.1 Scenario 1

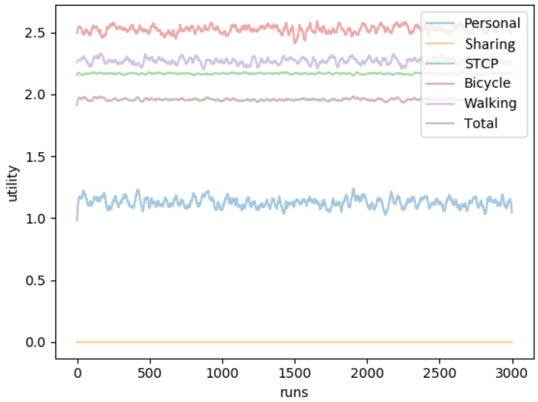
D.1.1 Run 1





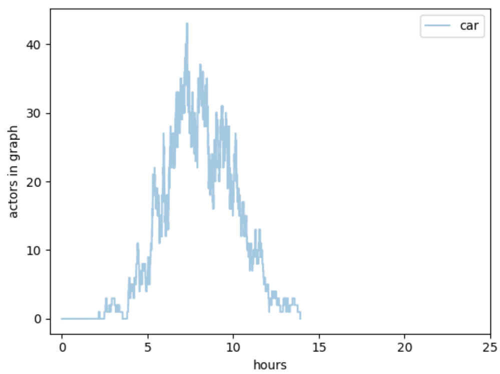


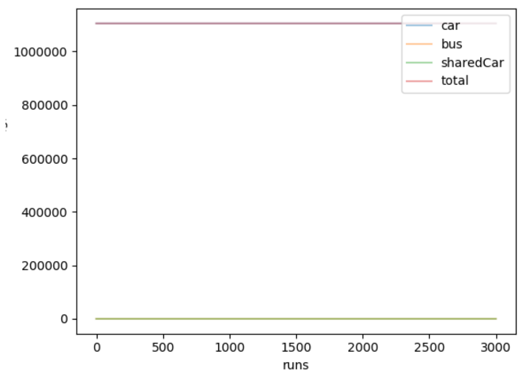


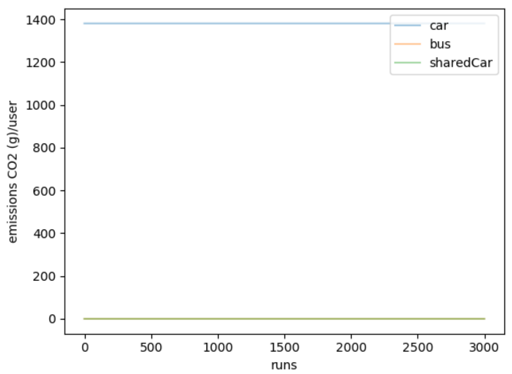


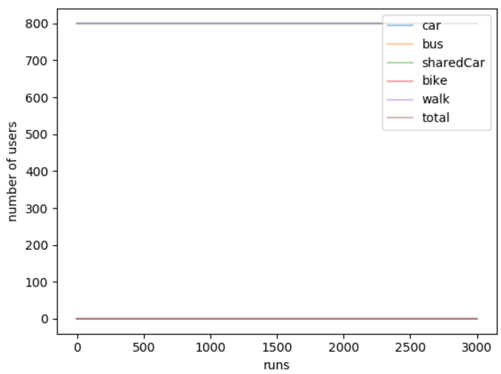
D.2 Scenario 2

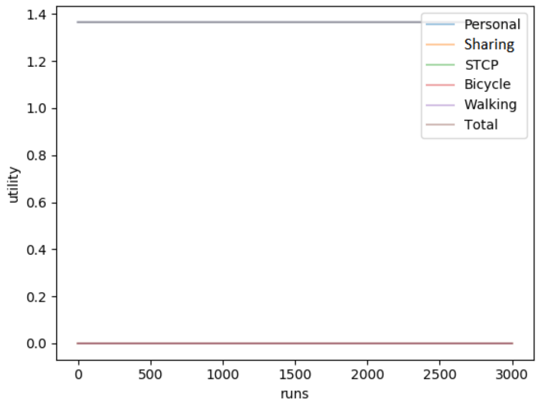
D.2.1 Run 1





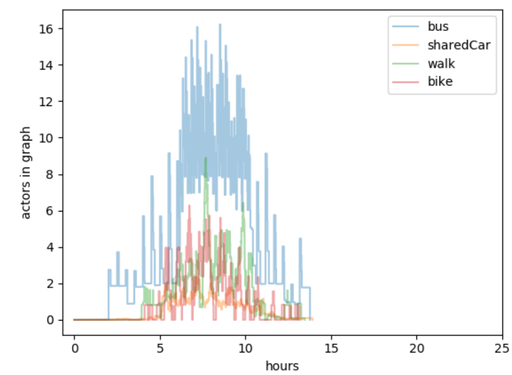


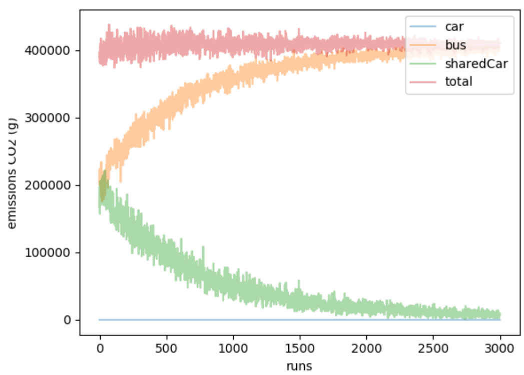


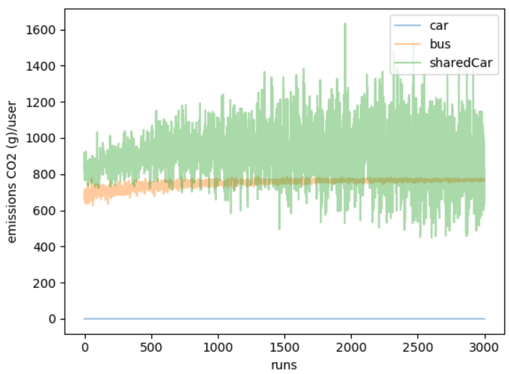


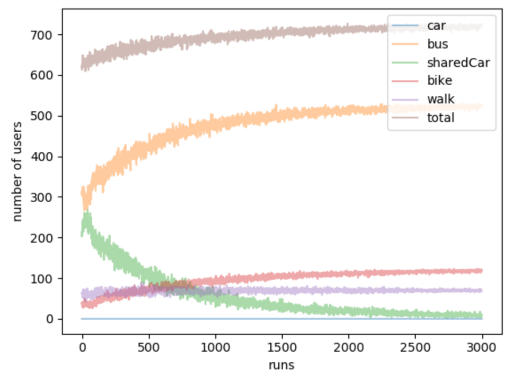
D.3 Scenario 3

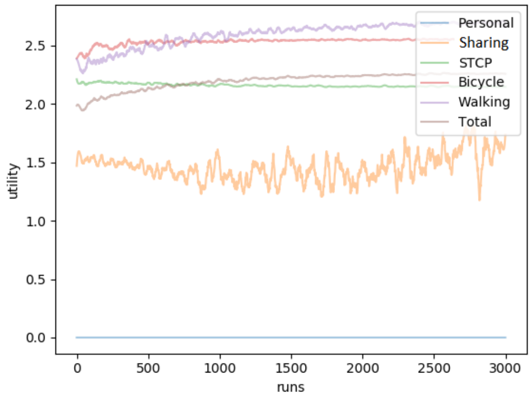
D.3.1 Run 1



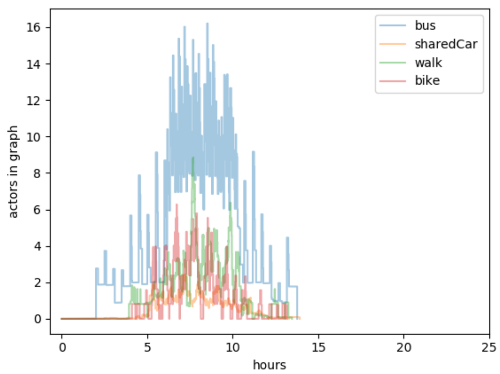


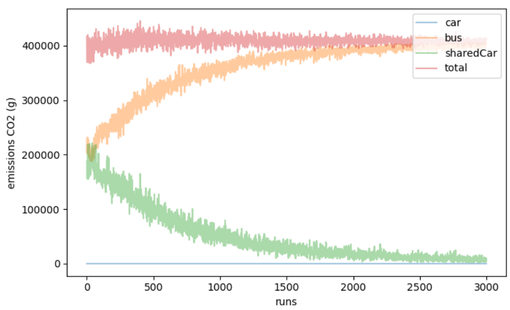


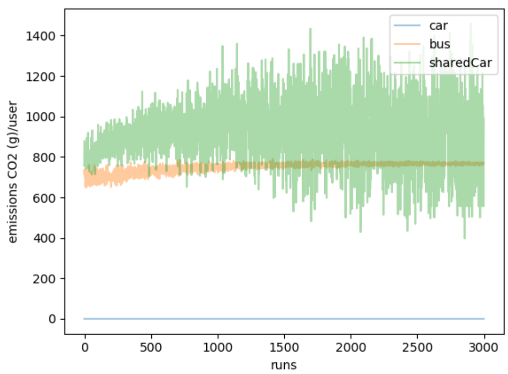


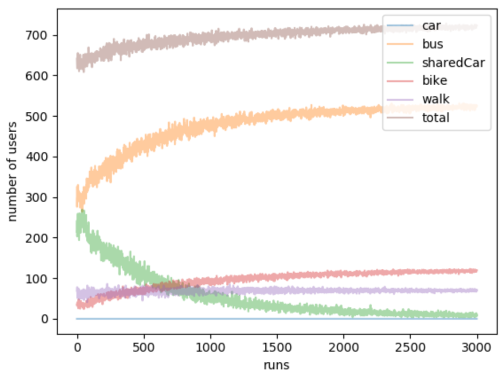

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

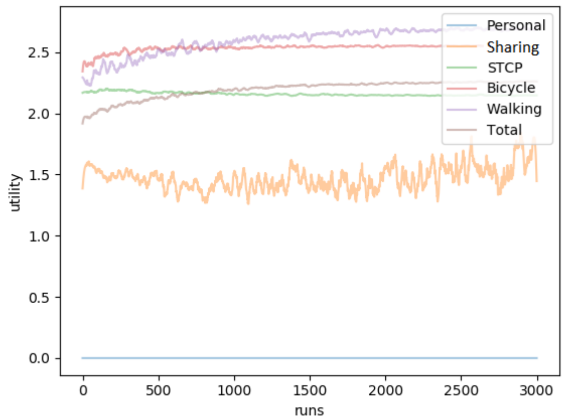
D.3.2 Run 2


bus
sharedCar
walk
bike
actors in graph
hours

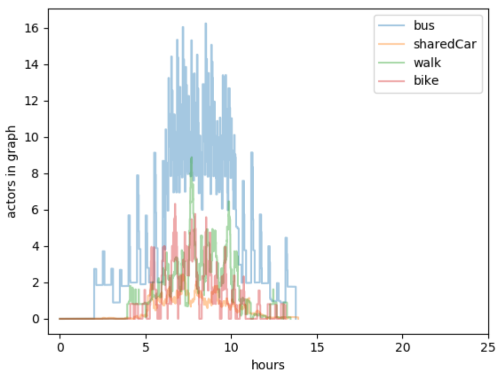

car
bus
sharedCar
total
emissions CO2 (g)
runs

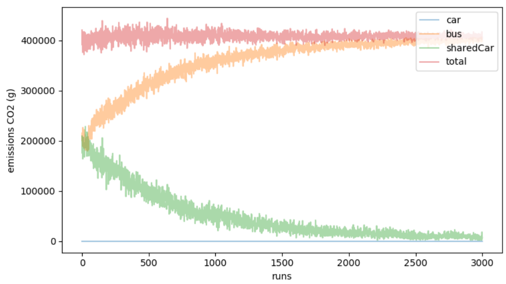

car
bus
sharedCar
emissions CO2 (g)/user
runs

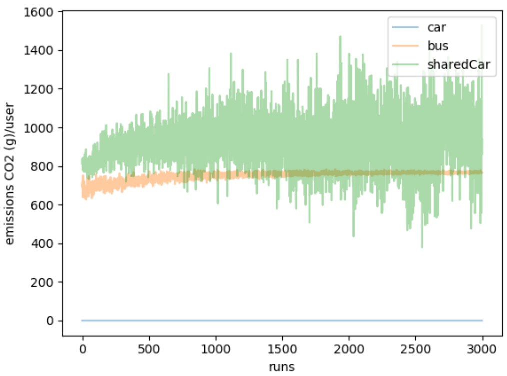

car
bus
sharedCar
bike
walk
total
number of users
runs

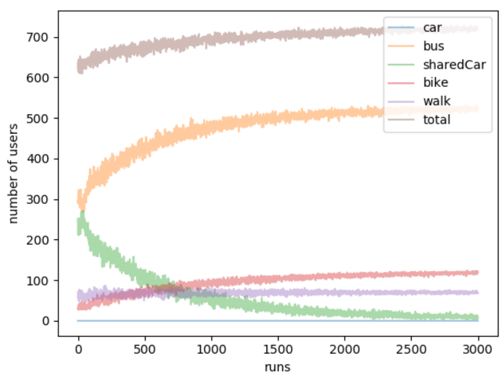

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

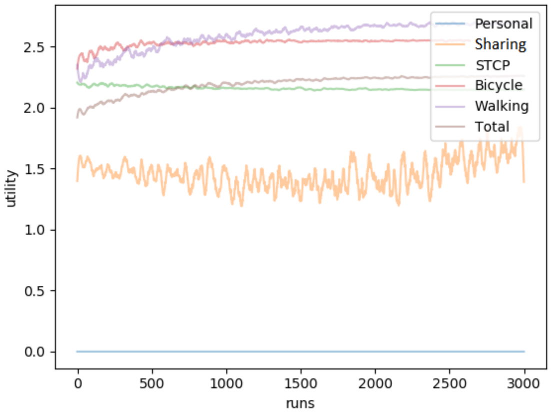
D.3.3 Run 3


bus
sharedCar
walk
bike
actors in graph
hours


car
bus
sharedCar
total
emissions CO2 (g)
runs

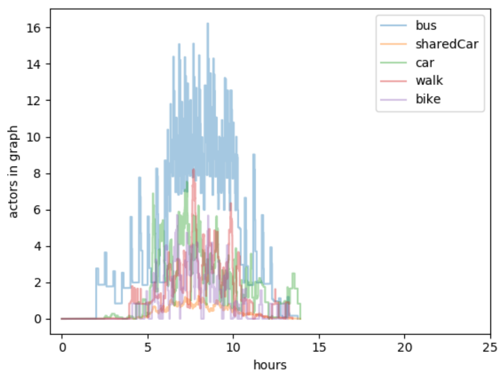

car
bus
sharedCar
emissions CO2 (g)/user
runs

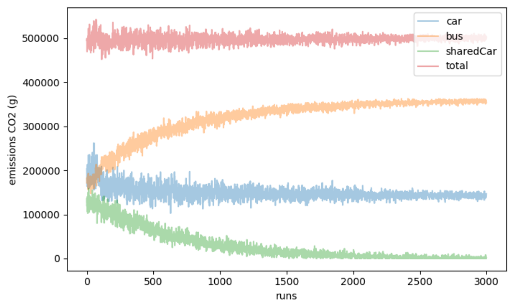

car
bus
sharedCar
bike
walk
total
number of users
runs

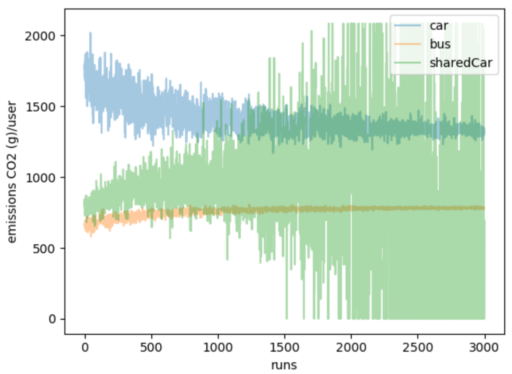


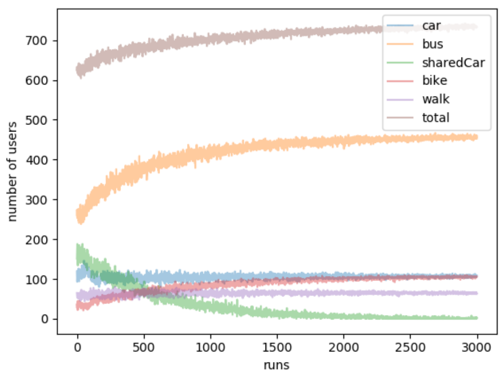
D.4 Scenario 4

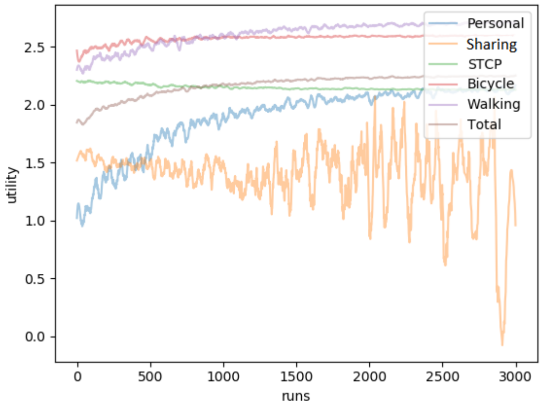
D.4.1 Run 1



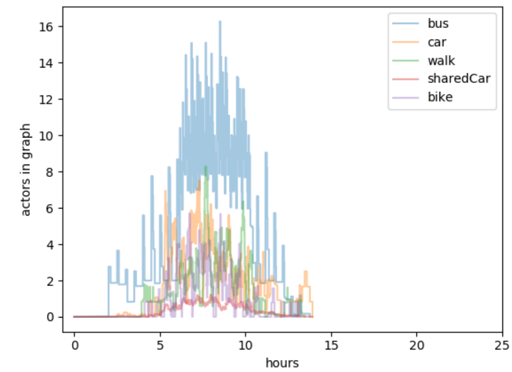


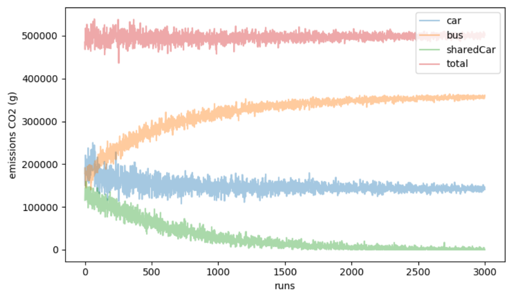


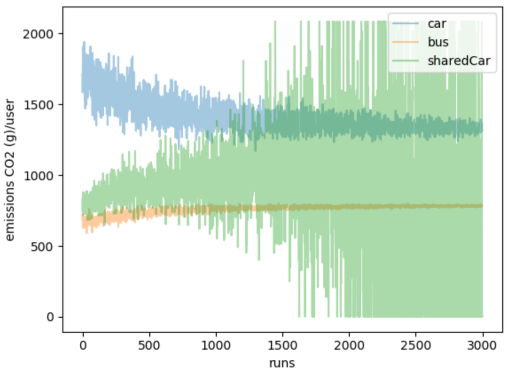


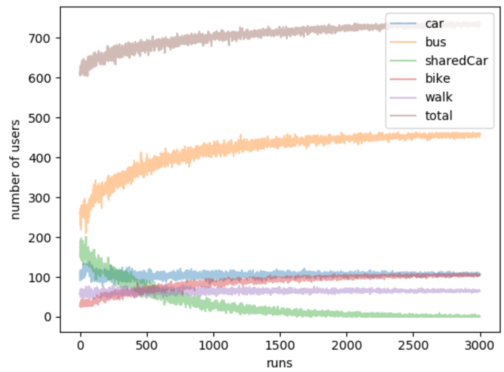

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

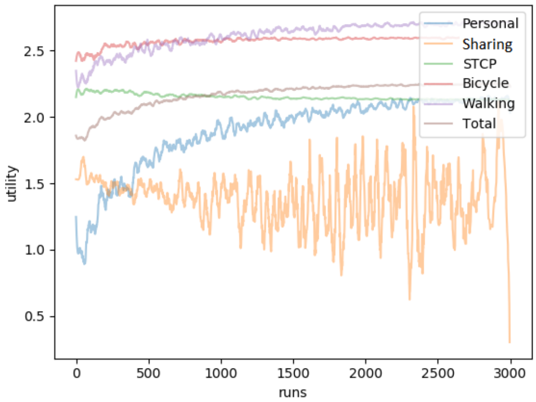
D.4.2 Run 2


bus
car
walk
sharedCar
bike
actors in graph
hours

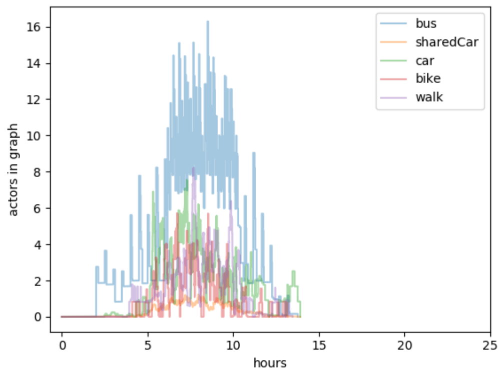

car
bus
sharedCar
total
emissions CO2 (g)
runs

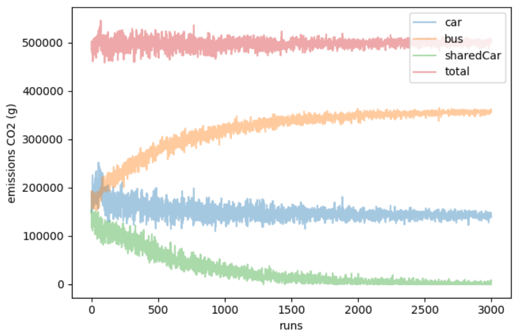

car
bus
sharedCar
emissions CO2 (g)/user
runs

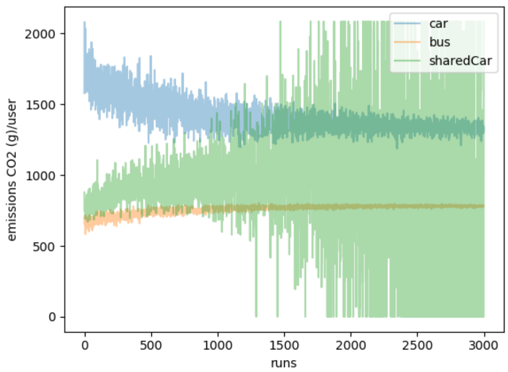

car
bus
sharedCar
bike
walk
total
number of users
runs

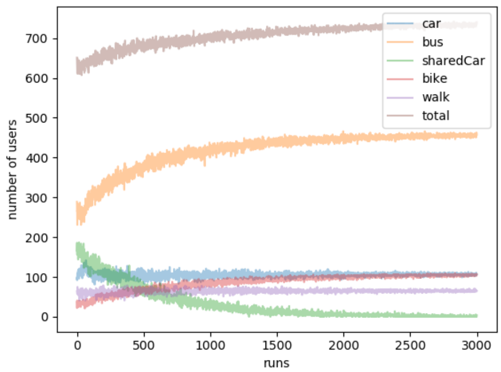

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

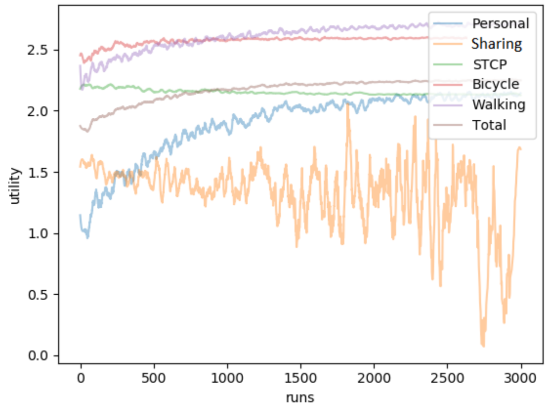
D.4.3 Run 3


bus
sharedCar
car
bike
walk
actors in graph
hours


car
bus
sharedCar
total
emissions CO2 (g)
runs

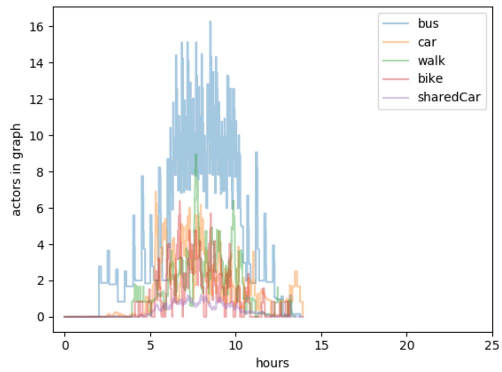

car
bus
sharedCar
emissions CO2 (g)/user
runs

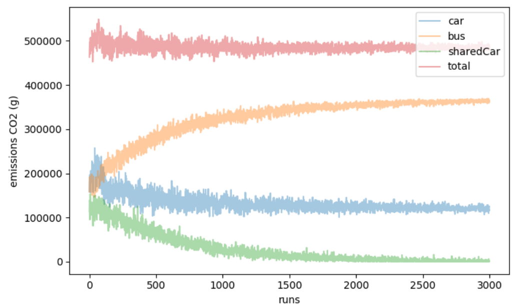

car
bus
sharedCar
bike
walk
total
number of users
runs

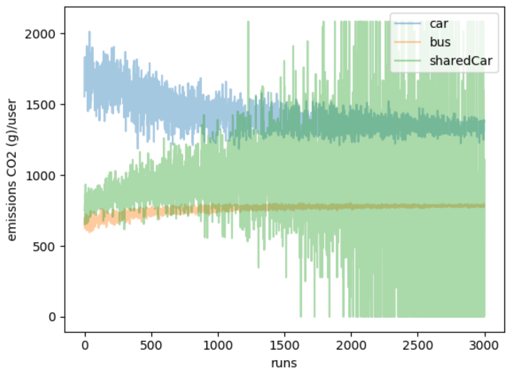


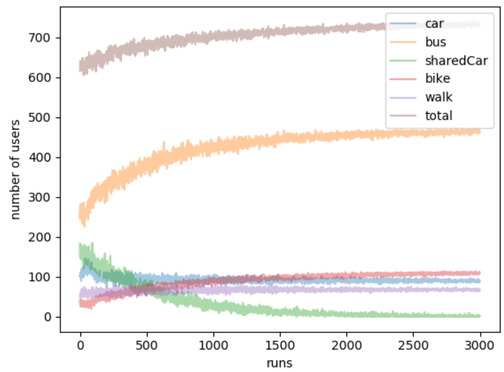
D.5 Scenario 5

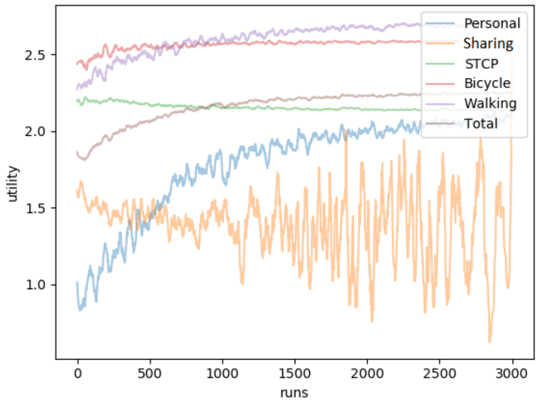
D.5.1 Run 1



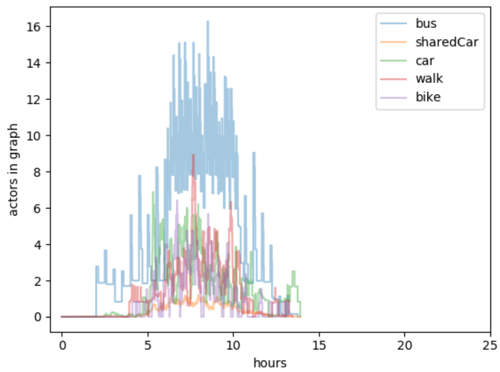


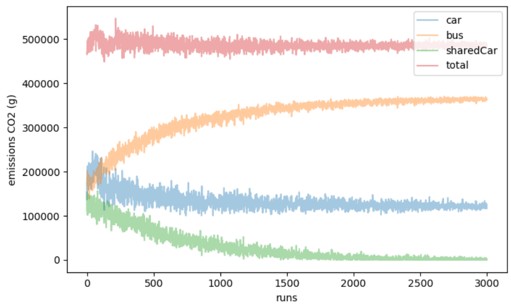


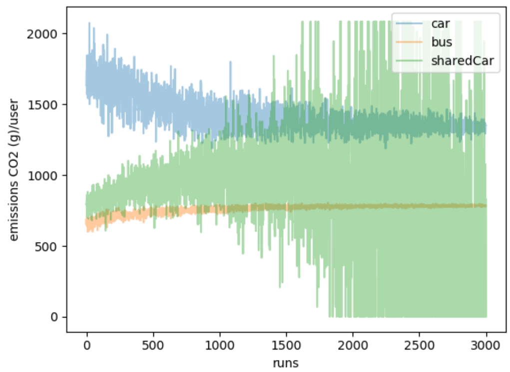


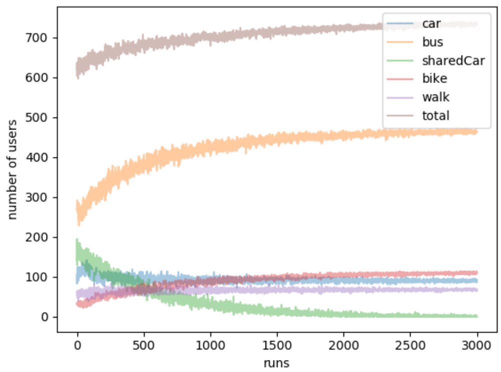

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

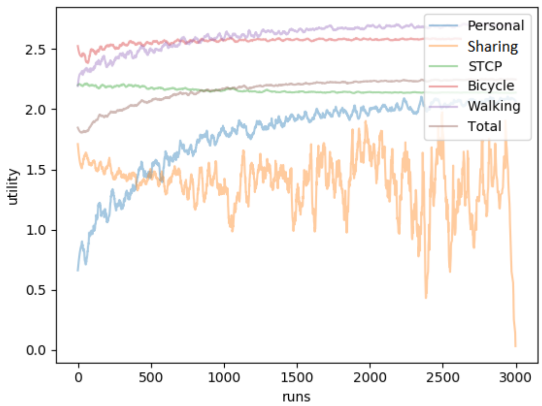
D.5.2 Run 2


bus
sharedCar
car
walk
bike
actors in graph
hours

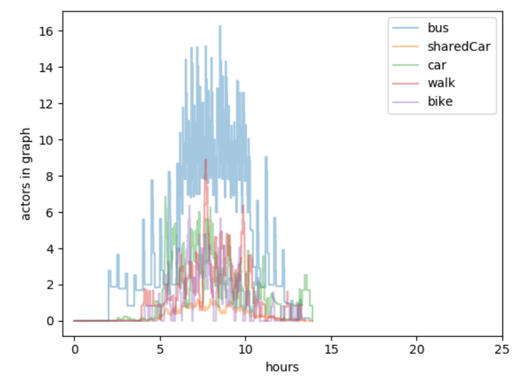

car
bus
sharedCar
total
emissions CO2 (g)
runs

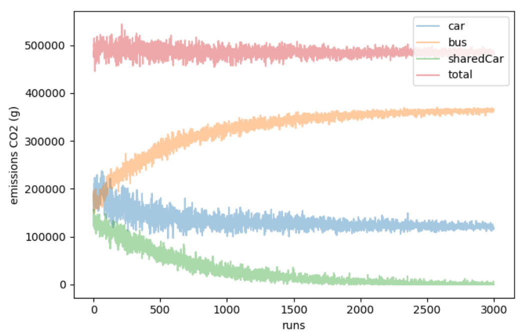

car
bus
sharedCar
emissions CO2 (g)/user
runs

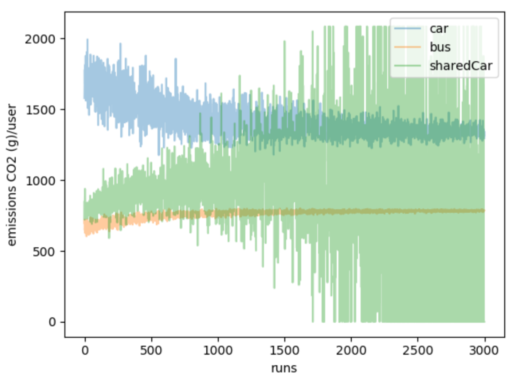

car
bus
sharedCar
bike
walk
total
number of users
runs

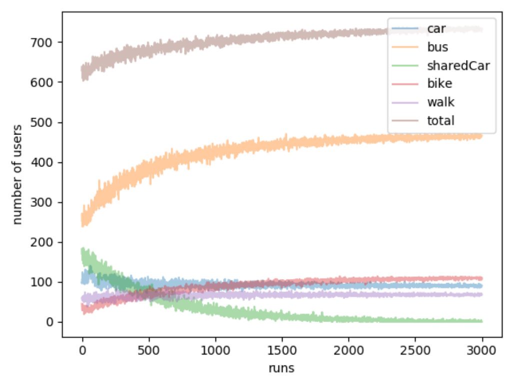

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

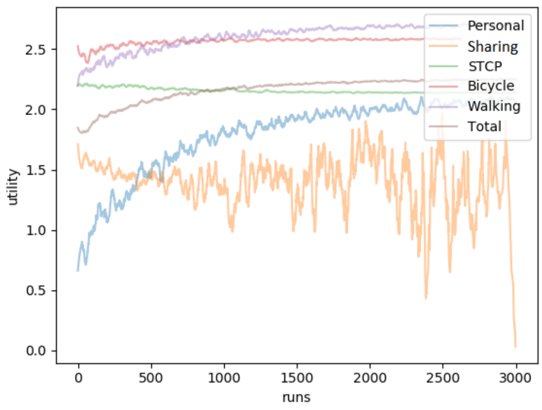
D.5.3 Run 3


bus
sharedCar
car
walk
bike
actors in graph
hours


car
bus
sharedCar
total
emissions CO2 (g)
runs

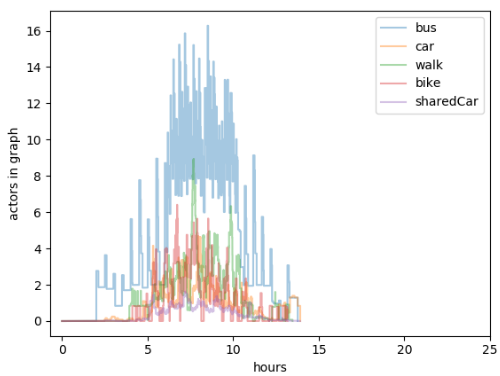

car
bus
sharedCar
emissions CO2 (g)/user
runs

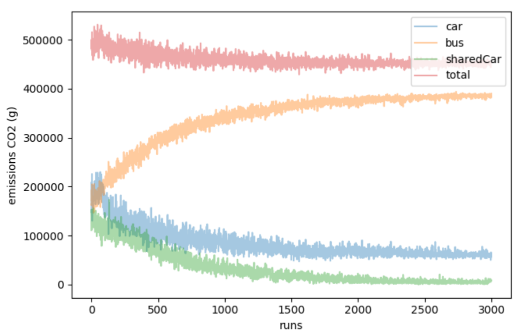

car
bus
sharedCar
bike
walk
total
number of users
runs

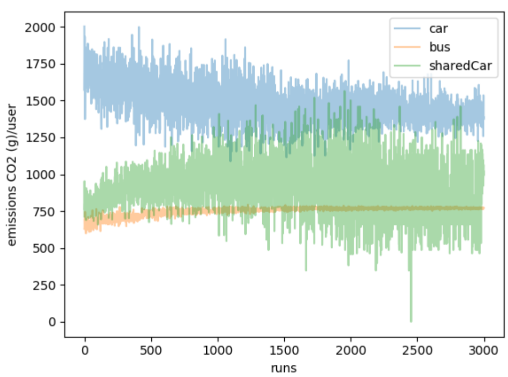


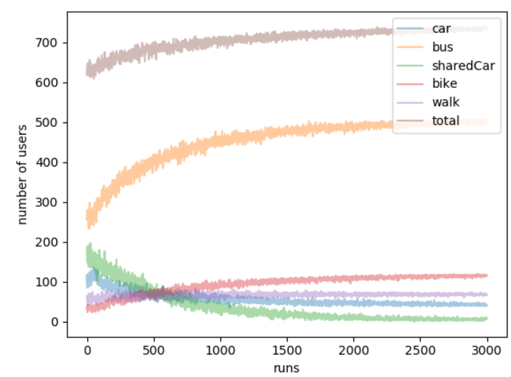
D.6 Scenario 6

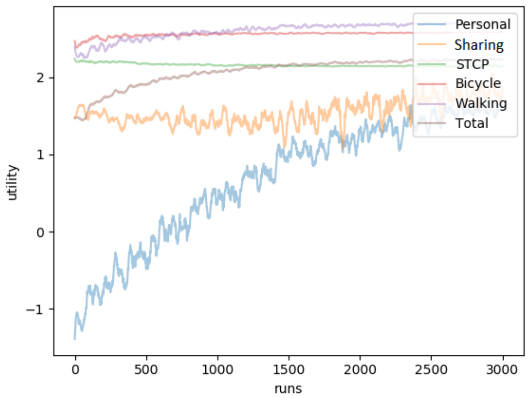
D.6.1 Run 1



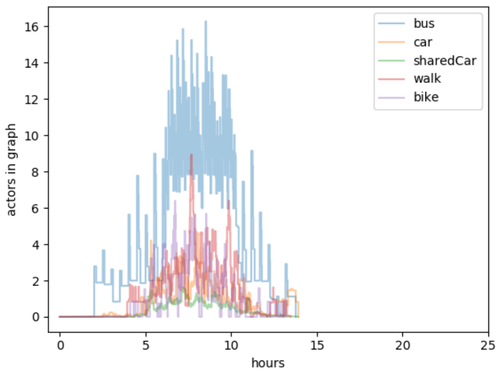


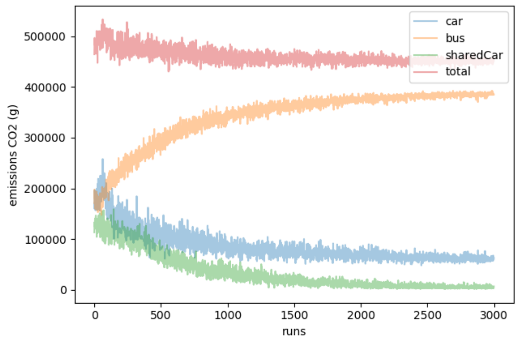


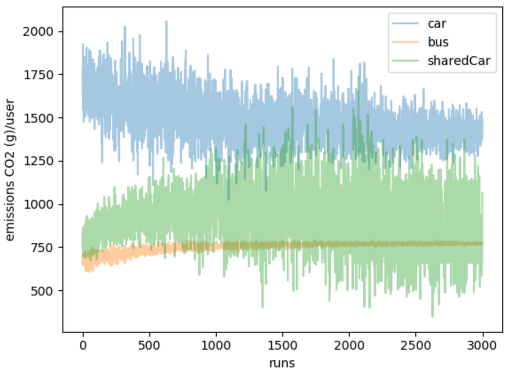


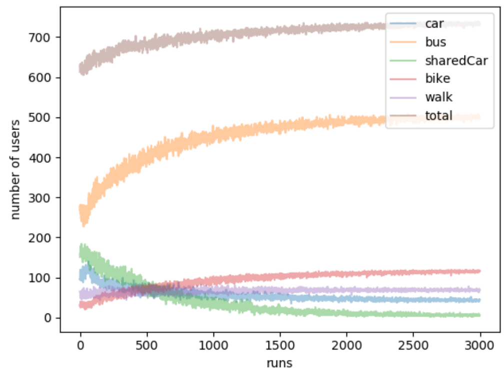

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs
−1
0
1
2
0
500
1000
1500
2000
2500
3000

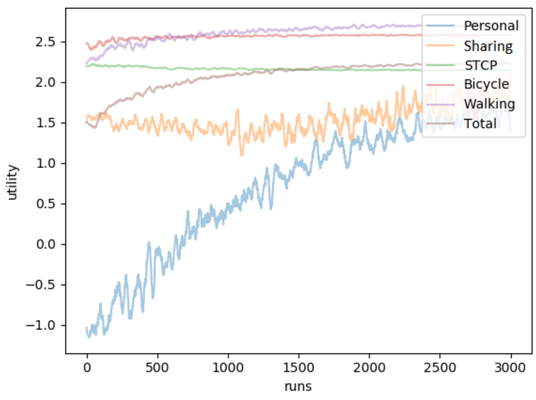
D.6.2 Run 2


bus
car
sharedCar
walk
bike
actors in graph
hours
0
2
4
6
8
10
12
14
16
0
5
10
15
20
25

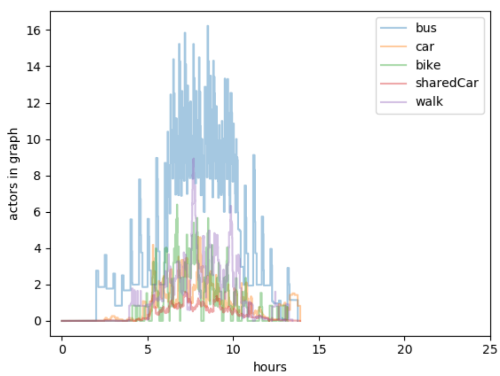

car
bus
sharedCar
total
emissions CO2 (g)
runs
0
100000
200000
300000
400000
500000
0
500
1000
1500
2000
2500
3000

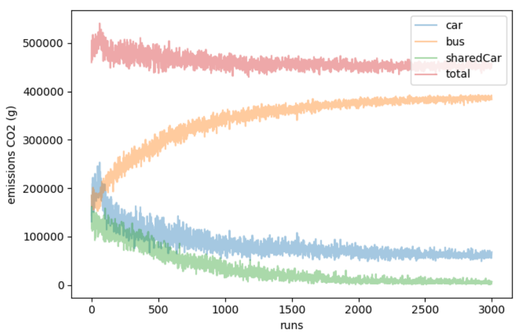

car
bus
sharedCar
emissions CO2 (g)/user
runs
500
750
1000
1250
1500
1750
2000
0
500
1000
1500
2000
2500
3000

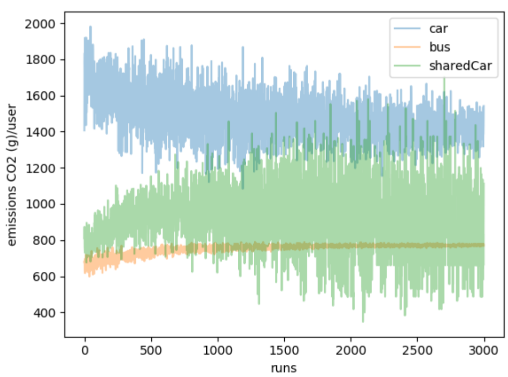

car
bus
sharedCar
bike
walk
total
number of users
runs
0
100
200
300
400
500
600
700
0
500
1000
1500
2000
2500
3000

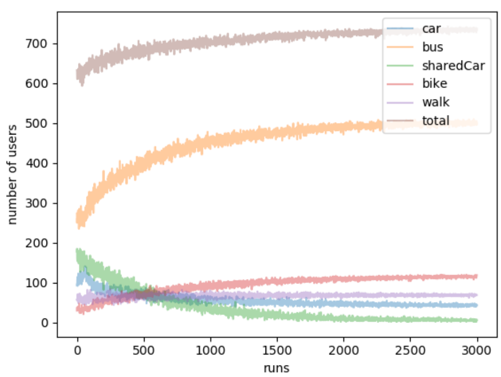

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

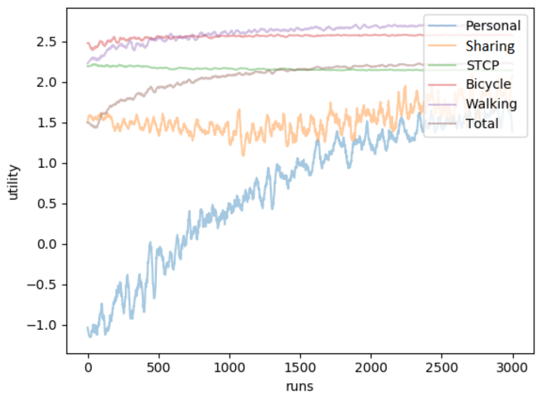
D.6.3 Run 3


bus
car
bike
sharedCar
walk
actors in graph
hours


car
bus
sharedCar
total
emissions CO2 (g)
runs

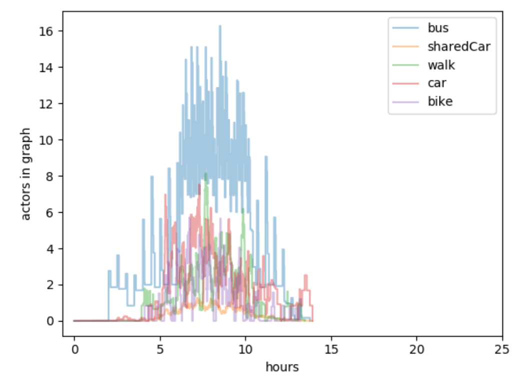

car
bus
sharedCar
emissions CO2 (g)/user
runs

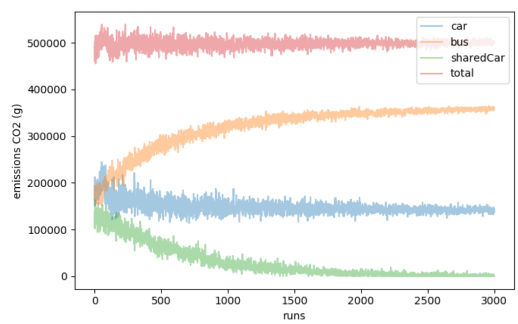

car
bus
sharedCar
bike
walk
total
number of users
runs

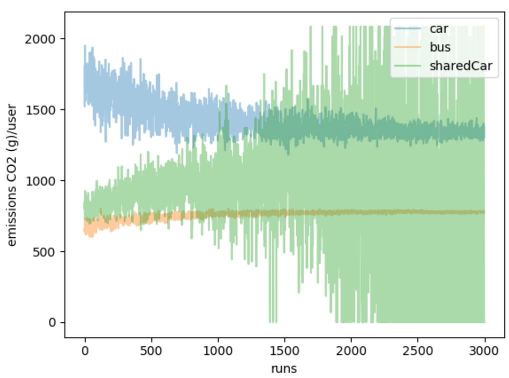


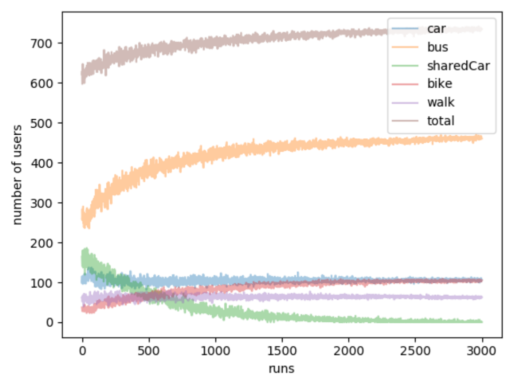
D.7 Scenario 7

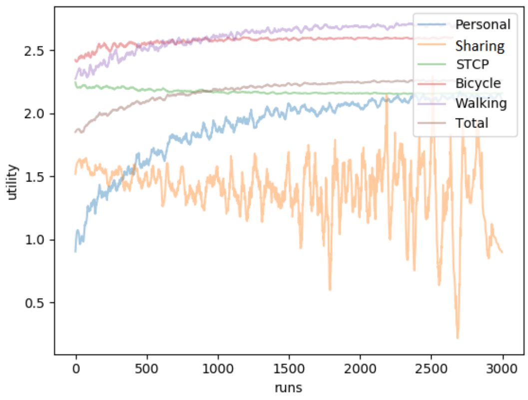
D.7.1 Run 1



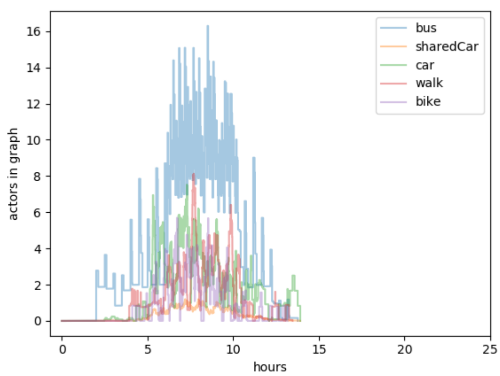


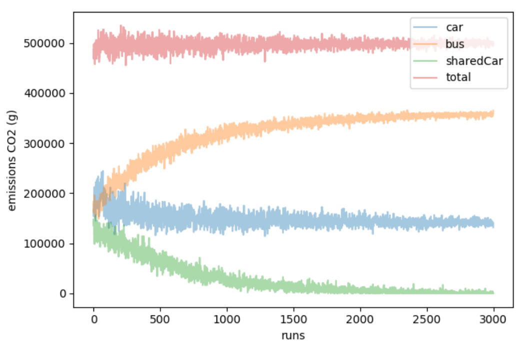


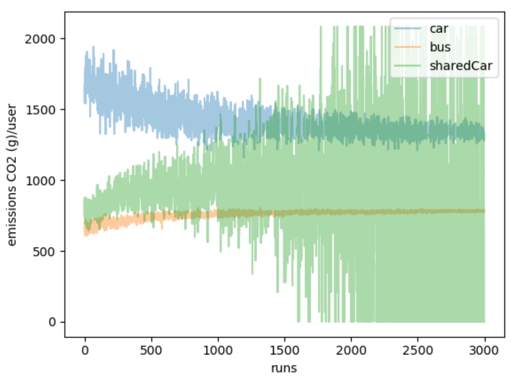


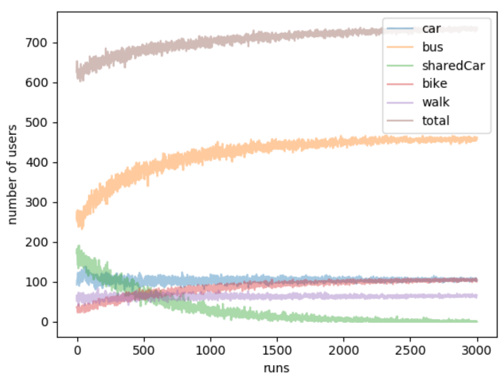

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

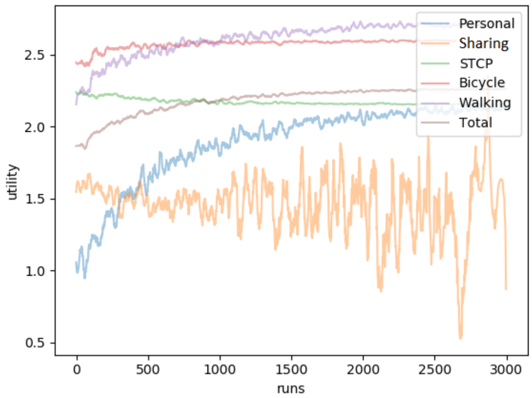
D.7.2 Run 2


bus
sharedCar
car
walk
bike
actors in graph
hours

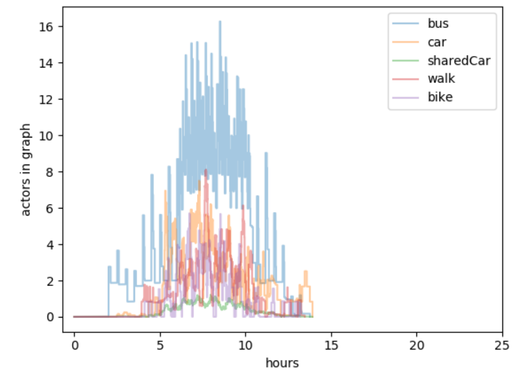

car
bus
sharedCar
total
emissions CO2 (g)
runs

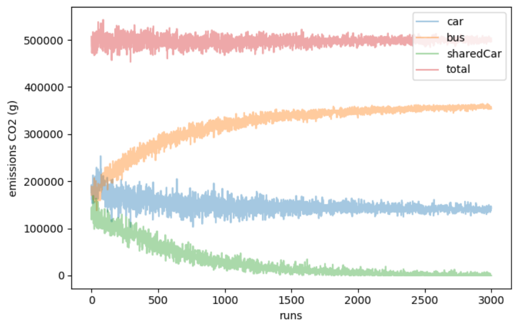

car
bus
sharedCar
emissions CO2 (g)/user
runs

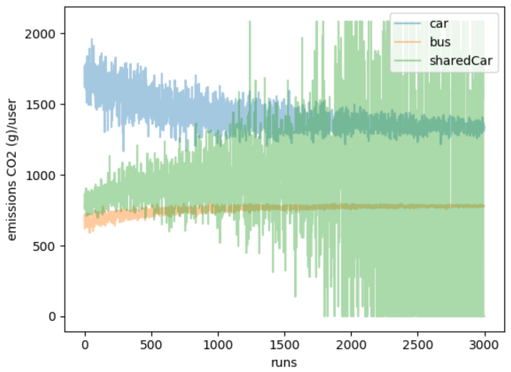

car
bus
sharedCar
bike
walk
total
number of users
runs

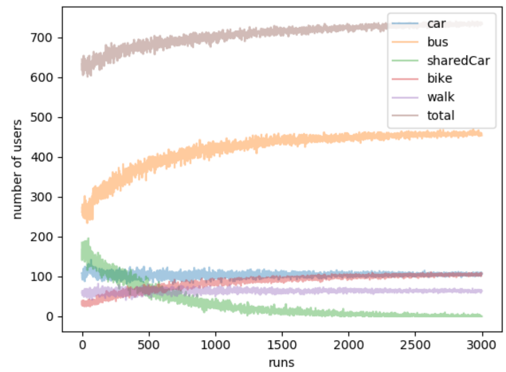

utility
runs
Personal
Sharing
STCP
Bicycle
Walking
Total

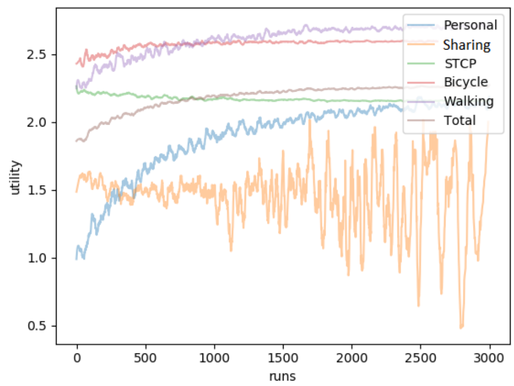
D.7.3 Run 3


actors in graph
hours
bus
car
sharedCar
walk
bike


emissions CO2 (g)
runs
car
bus
sharedCar
total

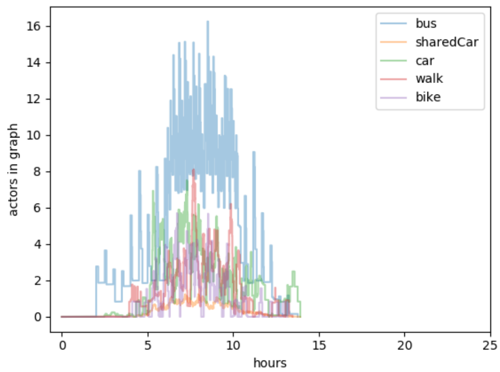

emissions CO2 (g)/user
runs
car
bus
sharedCar

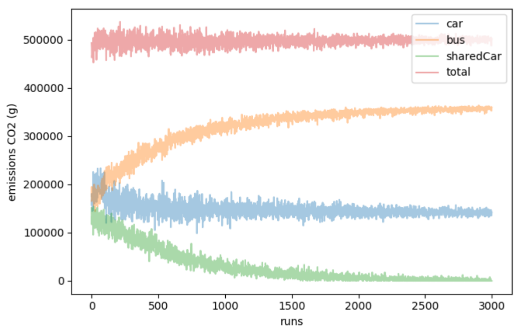

number of users
runs
car
bus
sharedCar
bike
walk
total

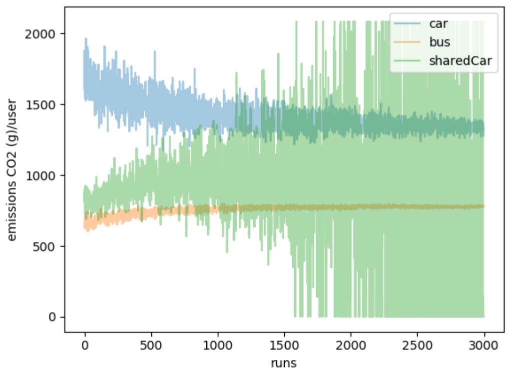


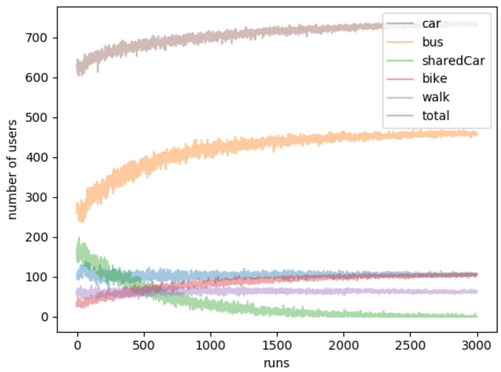
D.8 Scenario 8

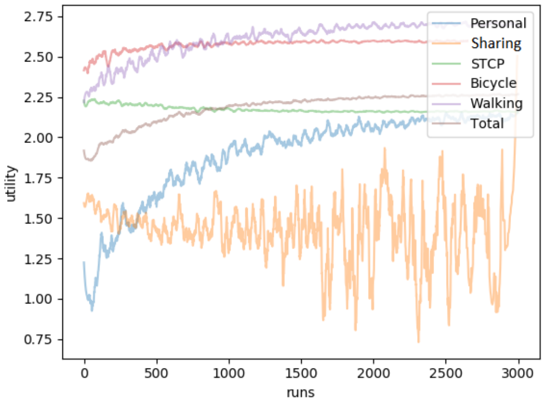
D.8.1 Run 1



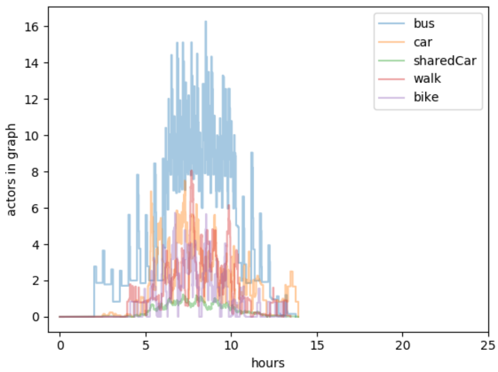


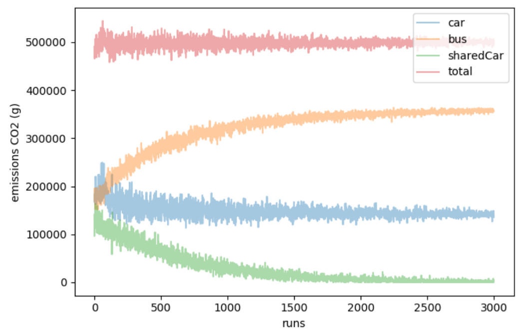


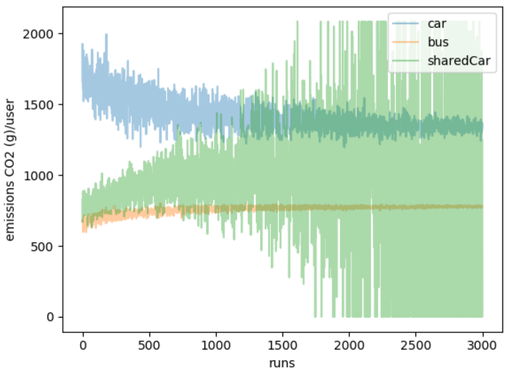


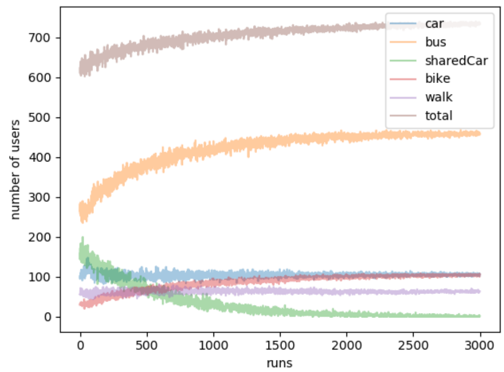

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

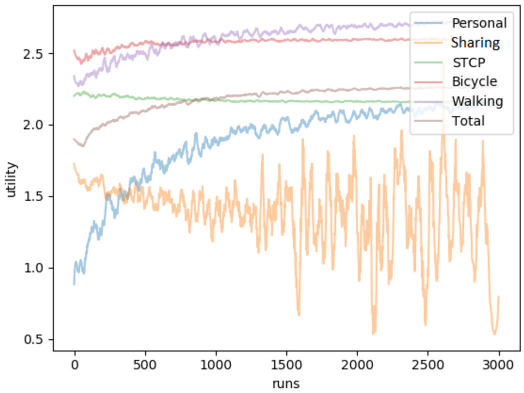
D.8.2 Run 2


bus
car
sharedCar
walk
bike
actors in graph
hours

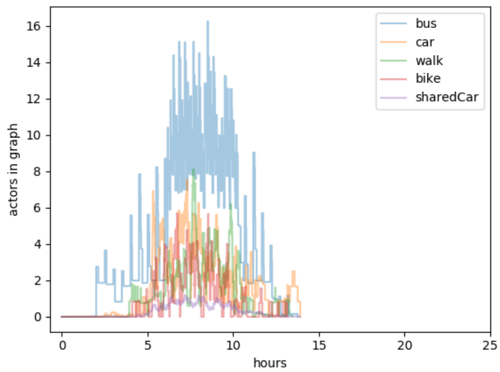

car
bus
sharedCar
total
emissions CO2 (g)
runs

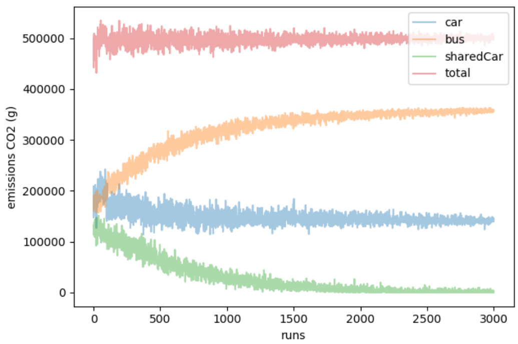

car
bus
sharedCar
emissions CO2 (g)/user
runs

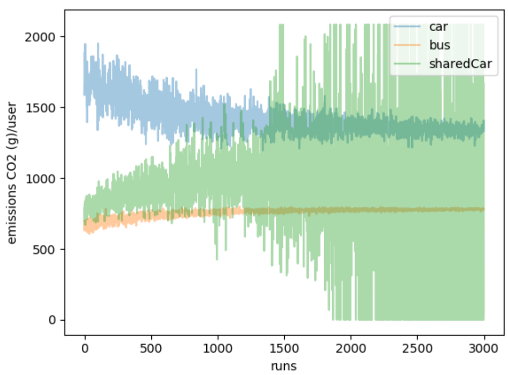

car
bus
sharedCar
bike
walk
total
number of users
runs

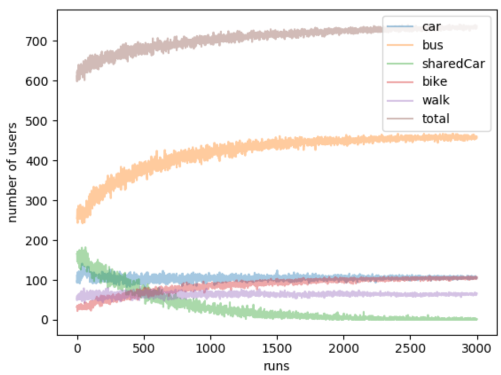

Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs

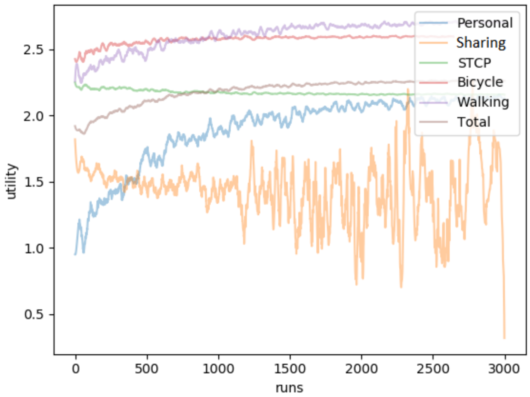
D.8.3 Run 3


bus
car
walk
bike
sharedCar
actors in graph
hours


car
bus
sharedCar
total
emissions CO2 (g)
runs


car
bus
sharedCar
emissions CO2 (g)/user
runs


car
bus
sharedCar
bike
walk
total
number of users
runs


Personal
Sharing
STCP
Bicycle
Walking
Total
utility
runs
0.5
1.0
1.5
2.0
2.5
0
500
1000
1500
2000
2500
3000

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