

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Combining System Dynamics and Agent-based Approaches to model Urban Mobility

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Abstract

The percentage of the population living in urban areas has grown and it is projected to continue to grow in the following years. The rapid influx of people into cities leads to growth in traffic volumes, resulting in increased congestion, emissions, and pollution. This leads to the need for transportation systems that satisfy the mobility needs of citizens.

In response, the European Commission encourages the implementation of Sustainable Urban Mobility Planning (SUMP), which focuses on data-based decision-making and coordinating of policies between sectors to achieve multi-modal, safe, sustainable, inclusive, and accessible mobility for all citizens.

Hybrid Approaches between System Dynamics with Agent-Based Modeling and Discrete Event Simulation have been gaining new relevancy in the literature, but have not yet been tested to model urban mobility. System Dynamics is a modeling approach created by Jay W Forrester in 1957. It focuses on feedback loops instead of the open-loop, event-oriented view of the world. Since then it has evolved and had major contributions in strategy and policy design. Agent-based modeling is used to represent heterogeneous behavior based on agents with simple rules that interact with each other and with their environment.

This dissertation presents a model based on System Dynamics principles, complemented by an Agent-Based modal choice model. It represents the main subsystems of a city, such as Population, Economy, Infrastructure, and Greenhouse Gas Emissions, through System Dynamics modeling. The Agent-Based approach enables the representation of more complex modal choices than those typically associated with System Dynamics. It allows policymakers to test the impact of policies on modal choice, evaluating responses from different population groups. The model provides clear indicators inspired by the priorities and guidelines set by the European Commission.

This solution enhances policymakers' ability to understand and measure current transportation systems, provides insights into potential improvements, and allows for direct policy evaluation, making it a valuable tool in the decision-making process.

Keywords: System Dynamics, Mobility Plan, Artificial Society, Intelligent Transportation System, SUMP, Agent-Based model, Hybrid model, Multi-paradigm modeling

ACM Classification: Computing methodologies: Modeling and simulation: Simulation types and techniques: Agent / discrete models; Computing methodologies: Artificial intelligence: Distributed artificial intelligence: Multi-agent systems; Applied computing: Operations research: Transportation;

Resumo

A percentagem da população que vive em áreas urbanas tem aumentado e prevê-se que continue a crescer nos próximos anos. O rápido influxo de pessoas para as cidades leva ao crescimento dos volumes de tráfego, resultando em maior congestionamento, emissões e poluição. Isso está na origem da necessidade de sistemas de transporte que satisfaçam as necessidades de mobilidade dos cidadãos.

Em resposta, a Comissão Europeia incentiva a implementação de Planos de Mobilidade Urbana Sustentável (PMUS), que se concentram na tomada de decisões baseadas em dados e na coordenação de políticas entre setores para alcançar uma mobilidade multimodal, segura, sustentável, inclusiva e acessível para todos os cidadãos.

Abordagens híbridas entre System Dynamics, Agent-Based Modeling e Discrete Event Simulation têm ganho nova relevância na literatura, mas ainda não foram testadas para simular a mobilidade urbana. System Dynamics é uma abordagem de simulação criada por Jay W. Forrester em 1957. Ela foca em feedback loops em vez da visão de mundo orientada por eventos. Desde então, evoluiu e teve grandes contribuições na formulação de estratégias e políticas. A modelagem baseada em agentes (Agent-Based Modeling) é utilizada para representar comportamentos heterogêneos com base em agentes com regras simples que interagem entre si e com o ambiente.

Esta dissertação apresenta um modelo baseado nos princípios de System Dynamics, complementado por um modelo de escolha modal baseado em agentes. Os principais subsistemas de uma cidade, como População, Economia, Infraestrutura e Emissões de Gases de Efeito Estufa, são representados através de System Dynamics. A abordagem baseada em agentes permite a representação de escolhas modais mais complexas do que as tipicamente associadas ao System Dynamics. Isso possibilita a analistas testar o impacto de políticas sobre a escolha modal, avaliando as respostas de diferentes grupos populacionais. O modelo fornece indicadores claros inspirados nas prioridades e diretrizes estabelecidas pela Comissão Europeia.

Esta solução aumenta a capacidade de analistas de compreender e medir os sistemas de transporte atuais, fornece insights sobre possíveis melhorias e permite uma avaliação direta das políticas, tornando-se uma ferramenta valiosa no processo de tomada de decisão.

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Marta Mariz

*“(...) tudo vale a pena,
tornar as almas mais pequenas é que não.”*

José Mário Branco

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Abbreviations and Symbols

AB	Agent-Based
SD	System Dynamics
M&S	Modelling and simulation
CLD	Causal Loop Diagram
GIS	Geo-spatial Information System
OD	Origin Destination pair in Matrix
SUMP	Sustainable Urban Mobility Plans
APE	Absolute Percentage Error
MAPE	Mean Absolute Percentage Error

Chapter 1

Introduction

1.1 Context and Motivation

The rapid growth of urban populations is an undeniable global trend. As more people migrate to urban areas in search of better opportunities and improved living standards, cities are experiencing unprecedented expansion. This urbanization trend is projected to continue in the coming years, posing significant challenges for urban mobility systems. The influx of people into cities results in increased traffic volumes, leading to severe congestion, longer travel times, and higher levels of emissions and pollution. These challenges underscore the need for effective and sustainable transportation systems that can accommodate the growing demand for mobility while minimizing environmental and social impacts.

Transportation is a major contributor to emissions, making it a vital component of the European Green Deal, which aims to reduce greenhouse gas emissions and achieve climate neutrality. In response, the European Commission advocates for the adoption of Sustainable Urban Mobility Planning (SUMP). SUMP emphasizes data-driven decision-making and coordinated policy efforts across various sectors to achieve multimodal, safe, sustainable, inclusive, and accessible mobility for all citizens. In Portugal, it is now mandatory for municipalities, intermunicipal communities, metropolitan areas, and functional urban centers to develop Sustainable Urban Mobility Plans. Despite this requirement, a study by [Instituto da Mobilidade e dos Transportes \(2023a\)](#) revealed that only 61% of the Portuguese entities surveyed had allocated planning resources to urban mobility. There is a pressing need for simulation tools that align with the goals of major international organizations and provide the necessary resources to describe and test the projected effects of mobility systems.

Aggregate modeling tools have been used to determine the long-term effects of certain policies on the complex global environment through 'what-if' scenarios. System Dynamics is a modeling approach based on feedback loops between subsystems. With recent computational developments, there has been growing interest in combining System Dynamics principles with other modeling approaches that better represent certain behaviors. For instance, hybrid models that integrate System Dynamics with Agent-Based Modeling and Discrete-Event Simulation offer a more nuanced

analysis by capturing individual behaviors along with the macro-level feedback loops. These hybrid approaches could provide more accurate simulations of urban mobility systems, allowing for a comprehensive evaluation of policy impacts.

This thesis represents a collaboration between FEUP, Faculdade de Engenharia da Universidade do Porto, ARMIS, a software development company situated in Porto, and ITA, a Brazilian university, aiming to develop a simulation model that can assess the effectiveness of mobility plans. The model is designed to integrate the specific indicators and goals of each city, ensuring its practical applicability in real-world scenarios.

1.2 Problem Definition

Mobility plans can be composed of various types of policies and impact numerous areas. There is no concrete defined format for what a mobility plan consists of, it affects cities unpredictably and is difficult to formalize. Given the heterogeneous nature of city elements and the policies that can be employed, to represent them accurately there is a need for modeling approaches that capture spatial features, citizens' behavior, the overall effects on gas emissions, etc. The challenge is to represent the various subsystems, their relationships, and dynamics to capture the real effects of policies in the overall system.

Hybrid models that integrate System Dynamics with Agent-Based Modeling and Discrete Event Simulation have been gaining attention recently but have not been widely applied to represent urban mobility comprehensively. In the System Dynamics models observed, modal choice is often simplified. However, how citizens react to the available transportation system is a crucial factor in determining the effects of policies. It is, therefore, relevant to explore more complex modal choices based on how an evolving population responds to changes in infrastructure.

This dissertation addresses the need for a comprehensive modeling tool that combines System Dynamics with Agent-Based Modeling to simulate urban mobility infrastructure, emissions, and related indicators. The proposed model aims to represent the interactions between these elements and their impact on each other, particularly focusing on modal choices made by individuals. Through System Dynamics it is possible to represent the evolving population based on the feedback loops that describe the conditions of the city. Through disaggregate modal choices, there is the added possibility to explore individual preferences when faced with infrastructure changes, how different groups react to policy, and get a more complex view of the urban mobility system.

1.3 Research Questions

This dissertation aims to respond to the following research questions and test the corresponding hypothesis.

- How can System Dynamics and Agent-Based modeling interact in a hybrid approach to represent mobility?

An approach where the main components of the city and indicators are modeled through System Dynamics, including the main feedback loops, combined with a modal choice based on a disaggregated Agent-Based approach can be developed, runs within a reasonable time, and can be used in the typical use cases associated with System Dynamics models.

- Does the hybrid approach improve the traditional evaluation of policy-making as supported by System Dynamics?

The integration of an Agent-Based modal choice allows for a new way to evaluate the effects of policy-making; this includes having a notion of space (given by origins and destinations) and the evaluation of how certain policies impact different groups of people.

1.4 Objectives

This dissertation aims to evaluate the representation capacity of a simulation tool based on System Dynamics principles combined with Agent-Based modal choice to represent urban mobility following the principles set by the European Commission. More specifically, the goals are to:

1. To develop a simulation tool that provides relevant indicators based on the principles dictated by SUMP.
2. To explore the capability of Hybrid Approaches to represent urban mobility models.
3. To explore the different modal choice models that can be integrated into the Hybrid Model.

1.5 Document Structure

This document is divided into six chapters, each structured to provide a comprehensive and organized view of the work developed in this dissertation. The goal is to guide the reader through the research, from foundational concepts to the final conclusions and implications. The dissertation begins with this introduction, which provides a concise overview of the context and goals of the research. This chapter sets the stage for understanding the challenges and motivations behind developing a simulation tool for urban mobility planning, highlighting its significance in the context of Sustainable Urban Mobility Planning.

Chapter 2 reviews existing literature on modeling approaches, urban mobility policy evaluation, and the current state of practice regarding the priorities of urban mobility. Each modeling approach is introduced by providing the essential background concepts necessary for understanding the work being developed. Then there is an exploration of the models available in the context of urban mobility, with a focus on the possibilities each approach brings to the representation of policy. These sections aim to identify current gaps and challenges in the field and establish a foundation for the contributions of this research. In Section 2.4, the mobility priorities at both the European and National levels are explored to ensure that the development of the simulation tool aligns with relevant policies and objectives, enhancing its practical applicability. This Chapter

ends with a summary of the main conclusions of the work explored, framing the proposed solution in both scientific and application contributions.

Chapter 3 describes the methodological approach used in the dissertation, detailing the modeling choices, priorities, and goals, and outlines the framework guiding the research.

Chapter 4 describes the implementation of the proposed model by dividing it into the System Dynamics Module, Agent-Based Module, and the Hybrid Approach, meaning the integration of the two models described. Section 4.1 describes the implementation of the System Dynamics Module, offering an in-depth look at its structure and functionality and detailing how system dynamics principles are applied to model urban mobility scenarios. Section 4.2 explores the development of modal choice models, highlighting how Agent-Based Modeling is used to represent individual travel behaviors and preferences. Section 4.3 explains how the System Dynamics and Agent-based modules are combined to form a cohesive simulation tool and details the technical and methodological aspects of this integration.

Chapter 5 presents possible use cases and the capabilities of the simulation tool through relevant case studies, demonstrating the practical application and effectiveness of the tool in assessing urban mobility scenarios in real-world contexts. Finally, Chapter 6 reflects on the main contributions of the dissertation, summarizing the research findings and their implications and discussing potential areas for future research, highlighting opportunities for further development and application of the simulation tool.

Chapter 2

Literature Review

This section aims to explore the main topics that provide a basis for the understanding of this dissertation. The first chapters will explore the main modeling approaches, their principles, examples regarding policy evaluation in urban or transportation scenarios, and the main limitations. The main focus will be System Dynamics approaches because they are the main theme of this dissertation, but there is major interest in the possibility of combining different approaches. It continues with an exploration of the state of practice regarding the relevant dimensions of mobility being explored on National and European levels. Finally, it concludes by framing the proposed solution with the gaps previously identified in both scientific and application domains.

2.1 System Dynamics

System dynamics is a common approach to modeling transportation systems due to its dynamic, flexible, and macro view of systems. This section aims to explore the main principles and components of the modeling approach and the relevant models regarding urban mobility.

2.1.1 Context

System Dynamics was created by J.W. Forrester at the end of the 1950s at MIT (Forrester, 1958). It marks the difference between making decisions through simple mental discrete models, where each event or decision has a clear consequence, and viewing them as a piece in a dynamic, evolving, and interconnected system (Stermann, 2000). To portray this, the approach is based on feedback, time delays, and stocks and flows.

The dynamics of a system are majorly determined by defining feedback loops. These can be positive (or self-reinforcing) and negative (or self-correcting). An example of the first is defining a Causal Loop Diagram, or CLD, modeling the number of eggs and chickens in a system. An increase in the number of chickens increases the number of eggs, which increases the number of chickens, and so on. It is self-reinforcing. In the case of chickens and chicken death by disease, the bigger the population of chickens, the bigger the risk for death, and the bigger the death rate, which causes a decrease in the population of chickens. It is a self-correcting loop.

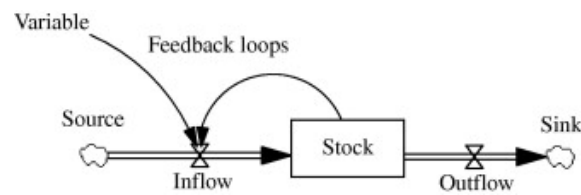


Figure 2.1: A simple System Dynamics model (Sterman, 2000).

The other major components are stocks and flows. Stocks characterize the state of the system and provide the basis for action. Flows characterize the rate of change of stocks. Sterman (2000) provides an example of a bathtub: the stock is the current water level, and flows are the water coming in and out of the bathtub.

The variables within the system can be endogenous, meaning their value is determined by other variables, or exogenous, meaning the system does not determine them, they have a given value. System dynamics seeks endogenous explanations for phenomenon (Sterman, 2000), therefore, the number of exogenous variables should be small.

Figure 2.1 represents the main elements described, it was borrowed from Sterman (2000).

In its beginnings, System Dynamics was mostly applied to corporate/managerial problems. "Urban Dynamics" by Forrester (1969) was one of the first major models outside this scope that proved the approach's applicability in urban studies and policy analysis.

Because the main structures of the approach capture the complex dynamics of real-world scenarios, it became a tool for multidisciplinary work with applications in various fields. Various systematic reviews have been done, including by Zanker et al. (2021), grouping recent papers by application domain. The reported applications were mainly in areas such as business (Kim and Chung, 2016), (Yu et al., 2019), (Wang et al., 2017), health (Kianmehr et al., 2020), (Best et al., 2016), (Rogers et al., 2018) and environment (Phonphoton and Pharino, 2019), (Phonphoton and Pharino, 2019), (Kotir et al., 2016), (Ha et al., 2017).

Policy making is an interesting and important area where System Dynamics has been applied and provided useful insight. The emphasis on feedback, changes over time, and the role of information delays helps inform policy makers about their choices' intended and unintended consequences (Andersen et al., 2020). Ghaffarzadegan et al. (2011) identify five major problems in policy making: Policy resistance from the environment, the cost of experimenting, the need to persuade different stakeholders, overconfident policymakers, and the need to have an endogenous perspective. They argue that System Dynamics models provide an interesting way to experiment with policies and their long-term impact on the environment, tackling self-serving biases and unsupported external influences.

The Urban Model is relevant in terms of the representation of city dynamics. It was adapted by John Sterman (Sterman, 1981) from the population-business (POPBSN) model in Introduction to Urban Dynamics (Alfeld and Alan, 1976). This book explores the ideas presented in Jay W. Forrester's Urban Dynamics book (Forrester, 1969), whose relevance has been mentioned above. Introduction to Urban Dynamics (Alfeld and Alan, 1976) explains the complexity of the urban

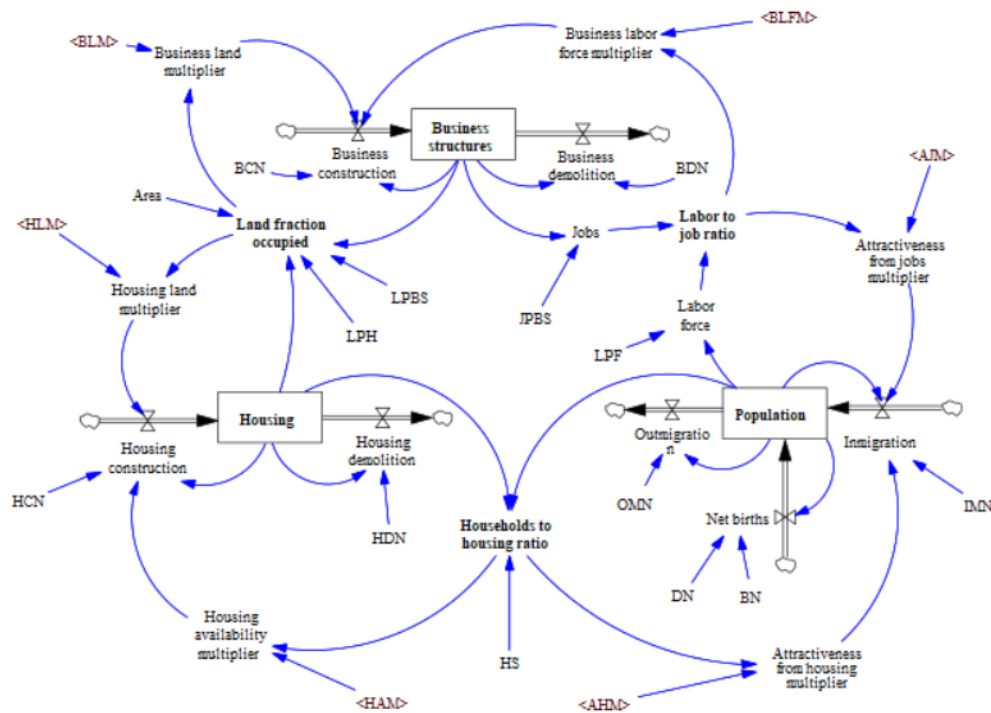


Figure 2.2: Vensim implementation of the Urban Model, (Stermann, 1981).

system by examining simpler urban subsystems one at a time. The Urban model is based on the idea of a city's life cycle, where a period of economic growth is followed by a period of transition toward equilibrium. It is a simple yet effective representation of the dynamics that move cities.

The model is split into three main sectors: Business Structures, Population, and Housing. It simulates and infers the future of an urban system through the interaction between these and the notion of a city's life cycle. The close relationship between jobs available and the labor force predicts job attractiveness and, with that, the growth of the Population through births and migration. If the conditions worsen and in the future there is less labor force available the Business Construction decreases, closing the loop. There is a similar interaction through land use between Housing, Business Structures, and the Housing Population; closed feedback loops in which key variables are endogenously defined. It is a great example of the capabilities of the approach to simulate complex systems through simple equation-based relationships. The model assumes a fixed value for a city's area, which simplifies real life. Analyzing growth with a fixed "Land Area" serves as a way to assume no city can expand indefinitely and study the types of pressures that can limit growth.

2.1.2 Model Characteristics

In the following subsections, models aiming to study urban mobility and how different policies impact it will be explored, highlighting the components relevant to the study.

System Dynamics is commonly used to test policy's effect on sustainable transportation. For example, [Sayadi and Awasthi \(2018\)](#) modeled the effects of different policies on CO₂ emissions, fuel consumption, and traffic congestion. [Haghshenas et al. \(2015\)](#) validated a model with multiple cities' data. They tested the effect of specific policies in the particular case of Isfahan, focusing on environmental, economic, and social effects. [Cheng et al. \(2015\)](#) develop a system dynamics model to test solutions for a sustainable urban transportation system. They simulate the effects of specific policies and explore their potential in reducing vehicular fuel consumption and, with that, mitigating CO₂ emissions. [Wang et al. \(2008\)](#) explore car ownership discouragement through policy and its effect on the environment and economy of Dalian, China. [Fontoura et al. \(2019\)](#) focus on testing the effect of implementing a specific Brazilian policy on the percentage of use of public transport, carbon dioxide emissions, and traffic congestion. [Akbari et al. \(2020\)](#) present a study aimed at determining the most important parameters of environmental pollutant emissions in the urban transport sector and developing the System Dynamics model of Tehran urban transport. [Procter et al. \(2017\)](#) in collaboration with local stakeholders, developed a System Dynamics model to simulate how Light Rail transit and concurrent policies could help Durham County reach the greenhouse gas emission goals they set by 2030. [Wiman et al. \(2022\)](#) focus on the qualitative variables that may change or reinforce transport usage, such as willingness to fit in, perceived safety, crowding, etc., to represent modal choice and how it may change. It is a different approach more focused on how to affect the citizen's modal choices and then how it impacts the system regarding greenhouse gas emissions.

It has also been used to test policies that could solve intense traffic congestion ([Suryani et al., 2020a](#)), ([Sayadi and Awasthi, 2018](#)), ([Fontoura et al., 2019](#)). [Suryani et al. \(2020a\)](#) use System Dynamics to predict the future of urban mobility in Surabaya regarding the current trends of traffic control policies.

System Dynamics is used to model vehicle preference in different conditions. [Vecchio et al. \(2019\)](#) models preferences of transportation mode when users have different priorities and the effect on the overall system. [Pokharel et al. \(2023\)](#) models different policies' capacities to discourage car usage and increase public transport dominance.

[Mayo et al. \(2022\)](#) aim to ensure commuter safety while requiring a reasonable budget and use System Dynamics to represent the city and possible fatalities.

There is also an interest in exploring land use transport interaction and what representation possibilities the approach provides. [Pfaffenbichler \(2010\)](#) present the logic behind the model MARS. It comprises various highly specific sub-models regarding land use, transport usage, workplace locations, and emissions. There is a constant focus on supply and demand to reach the equilibrium representing a city's dynamics. It presents a complex and highly descriptive model and possible policy implementations.

[Fiorello et al. \(2010\)](#) do not present specific policies; they present the possibilities of the ASTRA model, a very detailed System Dynamics model, to assess transport policies. It joins System Dynamics with origin-destination matrices and the types of trips regarding purpose to more accurately represent modal split. It is specially designed to answer Europe's transportation

needs, providing many indicators as outputs.

There were two main approaches to validate the relationships between variables: do correlation analysis with existing data or justify based on existing literature. Haghshenas et al. (2015) used SPSS18.0 and GAUSS14, Mayo et al. (2022) used IBM SPSS Statistics 21, Wang et al. (2008) mention performing correlation analyses, but they do not specify the software, Cheng et al. (2015) do a mix of regression analysis and decisions based on existing literature. On the other hand, Pokharel et al. (2023) and Fontoura et al. (2019) justify the correlations with the existing literature by providing the concrete articles they got it from.

2.1.3 Subsystem analysis

Modeling real-world problems comes with challenges, such as what to represent to capture accurate scenarios and obtain trustworthy predictions.

Different authors choose to represent different subsystems and variables. Table 2.1 explores what are the common dimensions represented in System Dynamics models. For example, to capture the current economy and to model direct feedback loops containing it Sayadi and Awasthi (2018), Haghshenas et al. (2015), Mayo et al. (2022), Wang et al. (2008) and Suryani et al. (2020b) choose GDP, whereas Pokharel et al. (2023) and Cheng et al. (2015) use personal income; The point is that all of them have a representation of economic growth throughout the years. Some common dimensions captured are economy, population, environment, and travel-supply. The goal of this analysis was to understand what researchers consider to be the main elements of a transportation system and its evolution through time.

Table 2.1: Comparison of represented dimensions in System Dynamics models.

	Economic	Population	Travel Demand	Environmental	Modal share module	Transportation Infrastructure	Law enforcement	Traffic congestion	External events	Land use
Sayadi and Awasthi (2018)	X	X	X	X		X				
Haghshenas et al. (2015)			X			X	X			
Mayo et al. (2022)	X	X		X		X	X			
Pokharel et al. (2023)	X		X			X				
Wang et al. (2008)	X	X	X	X		X		X		
Suryani et al. (2020b)		X	X		X	X		X	X	
Fontoura et al. (2019)	X	X	X	X		X		X		
Cheng et al. (2015)	X	X		X		X		X		
Pfaffenbichler (2010)		X	X	X	X	X		X		X
Akbari et al. (2020)	X	X	X	X		X				
Fiorello et al. (2010)	X	X	X	X	X	X		X		
Procter et al. (2017)	X	X	X	X				X		X
Wiman et al. (2022)			X	X		X				

2.1.4 Policy Modelling

Since the goal of this project is to provide a model that allows the representation of mobility plans, there is major interest in interpreting the ways policies are represented through System Dynamics. From the research developed, three different kinds of implementation were identified: Not representing the policy but the expected results in the system; policies with full representation that regard variables that were modeled; and quantifying the level of implementation of a plan that means controlling the number of vehicles on the road. In the next subsections, examples of these approaches will be presented to help understand how they appear in the literature.

2.1.4.1 Represent only the predicted effects of a policy

In many systems, the priority is to see how each policy's result would impact the rest of the system and not represent the policy itself.

There are many examples where the policy proposed is trip reduction or travel demand management (Sayadi and Awasthi, 2018), (Haghshenas et al., 2015), (Akbari et al., 2020), not a concrete policy that is doable in real life, but the expected result of certain policies.

Similarly, often investment in a certain transport mode, public transport, light rail, bike, etc., is represented as an increase in the share of trips for that specific mode and not as a change in infrastructure and response from the citizens (Haghshenas et al., 2015), (Cheng et al., 2015), (Procter et al., 2017). Most times, researchers justify these assumptions by representing patterns that have been seen in similar cities.

This kind of representation is also used with land usage policies. The control of urban sprawl or centralizing facilities and residential locations is represented as decreasing average trip distance (Sayadi and Awasthi, 2018), (Haghshenas et al., 2015), (Procter et al., 2017). It can be attributed to the lack of spatial representation of the approach.

In the literature, it was also found policies of investment in more efficient transport modes represented simply a reduction in the CO₂ emitted in the system (Haghshenas et al., 2015), (Akbari et al., 2020).

2.1.4.2 Policies with clear representation in the model

System Dynamics can represent infrastructure through quantitative values such as kilometers of road. Many researchers implement these policies directly by changing the increasing rate and observing the effects on traveler's responses. These policies include tramway, metro, and BRT network development (Haghshenas et al., 2015), increasing railway lines, and increasing the number of buses (Akbari et al., 2020). Another example is the change in road length, which directly affects congestion levels (Sayadi and Awasthi, 2018).

It is also possible to manipulate monetary values to see the influence on the system. There are multiple changes in car and public transport usage (Wiman et al., 2022) or investment in road maintenance that have a direct effect on the number of traffic-related accidents (Mayo et al., 2022).

In the model developed by Pfaffenbichler (2010), each transport mode has customizable attributes such as frequency, fares, attractiveness, etc. This allows for full customization of the changes in the transportation conditions in the system represented.

2.1.4.3 Representing the rate of implementation of a plan

System Dynamics was also used in the literature to represent the expected results after implementing a proposed plan. Fontoura et al. (2019) aimed to test the BUMP law, in the model the policy is represented as a value from 0 to 1 that directly affects the percentage of the population that utilizes public transport in their daily trips. In this example, the modal choice is changed artificially, and then the impacts on the rest of the system are observed.

To summarize, modeling policies in System Dynamics is not always a direct process. Many researchers model only the predicted effects of policies to see the effects on the overall system instead of modeling the concrete policy. There is interest in exploring the policies that have direct representation in the system as they are more complex and descriptive of the real-world scenarios in which this solution will be used.

2.1.5 Modal Choice

An important aspect of transportation systems is the choice of transport mode. Infrastructure changes only benefit society if the citizens respond well to said changes. Understanding the factors influencing transport mode choice is crucial for policymakers and urban planners aiming to promote sustainable transportation options and alleviate traffic congestion, air pollution, and other negative impacts of car dependency.

To address it, there was a focus on understanding the capabilities of modal choice in System Dynamics and what are the most common examples in the literature. The examples found will be divided into three sections: Modal share being manually changed, aggregate calculation based on infrastructure quality, and matrix-based.

2.1.5.1 Modal share as an implementation of policy

Many researchers opt to manually change the modal share of the systems and see the impact on the rest of the system. This can mean directly changing modal share implying a policy, for example, a vehicle restriction (Cheng et al., 2015), (Mayo et al., 2022), or implying that a policy's effectiveness or level of implementation is the only factor that directly affects modal share (Wang et al., 2008), (Fontoura et al., 2019).

2.1.5.2 Aggregate calculation based on infrastructure quality

A more complex method used in the literature is to define the modal share based on attributes that define the effectiveness of the transport system. Vecchio et al. (2019) focus on the population's priorities; based on their preferences, the weights of each attribute change, leading to different modal shares.

Akbari et al. (2020) represent direct connections between GDP and car use, bus trip conditions impacts bus trips, meaning that a change in each directly impacts modal share. Wiman et al. (2022) calculate feasible trips that set a maximum use of a mode for a given purpose, and this variable then defines the modal share. Feasibility has different meanings for each transport mode. Public transport feasibility is based on the availability of a connection for a trip purpose. Car feasibility is calculated based on the population's access to cars. Bike feasibility is based on the trip length. Procter et al. (2017) decided to focus on vehicle miles traveled; trips by public transport mean decreasing this number. Trips by public transport are influenced by the congestion described in the system, which is a more basic view of the system than the ones described above.

Haghshenas et al. (2015) implemented modal choice using the Multinomial Logit model. Each mode's utility is calculated using the conditions described in the system. Car utility is determined from car ownership, length of roads, parking spaces, vehicle speed of private transportation, and user's vehicle operating costs per income. Public transportation utility is calculated through the vehicle speed of public transportation, fleet size, access to exclusive routes, and user's trip costs per income. Shared taxis, railway, and bike shares are calculated using the same logic. All the weights for each parameter are calculated, guaranteeing high fidelity when compared to the models described. Multinomial Logit is capable of incorporating both characteristics of the passengers and the infrastructure and can be calibrated against real data.

2.1.5.3 Trips described through matrices

Some models have trips represented through origin and destination matrices to represent distances, trip purposes, and conditions described in different locations. Pfaffenbichler (2010) simulates passenger transport through trip generation, trip distribution, and mode choice. They are all calculated through a gravity (entropy-maximizing) type model. The researchers generate OD pairs, assign trip purposes, "commuting" or "other", and assign the modal share according to the conditions described in the model. The transport modes represented are walking, cycling, car, bus and rail. The ASTRA model by Fiorello et al. (2010) present a complex representation of transportation systems. They define different zones, and distance bands are used to determine which modes are available. Both passenger and freight transportation are considered. For passenger transport, walking and cycling, cars, buses, trains, and planes are considered. For freight transportation, only road, rail, and maritime. Travel cost and time are endogenously estimated depending on influencing factors like the structure of vehicle fleets, fuel price, fuel taxes, and congestion level, affecting the resulting modal split.

Predicting modal split and how it changes given the available infrastructure is essential to achieving reliable results when facing different scenarios. The frequent lack of representation of modal choice in System Dynamics is a clear flaw when describing transportation systems. Different policies can be tested when there is a more complex modal choice representation. Matrices seem to be a good method to ensure some spatial representation while still guaranteeing the efficiency observed in this approach.

2.1.6 Validation

To test and validate the models, the researchers tend to perform sensitivity analysis and validate with real data. Sensitivity analysis checks how different values of an independent variable affect a particular dependent variable under a certain set of assumptions. It is a common test performed among the literature reviewed (Sayadi and Awasthi, 2018), (Mayo et al., 2022), (Akbari et al., 2020), (Procter et al., 2017). Another common approach is to start the model at a previous time and compare the predicted values with the data available to prove the predictability capabilities of the model (Pfaffenbichler, 2010), (Akbari et al., 2020), (Wang et al., 2008), (Mayo et al., 2022), (Haghshenas et al., 2015). Validation is an important step in guaranteeing high fidelity in the results. The problem in some cases is guaranteeing the reliable data that allows this measure.

2.1.7 Current challenges and limitations

These are the current challenges of System Dynamics found in the literature:

- Incapability to include heterogeneous elements - The lack of ability to represent heterogeneous elements and behavior in the modeling approach is marked as a limitation by some authors (Łatuszyńska, 2020), (Nguyen et al., 2024). This may cause the need to complement with other modeling techniques to represent certain systems appropriately (Mashaly and Fernald, 2020).
- Not suitable for complex systems with unknown structures - According to Łatuszyńska (2020), because System Dynamics is equation-based and needs quantified relationships between variables, it is not as capable of representing systems with unknown structures (Łatuszyńska, 2020), (Mashaly and Fernald, 2020).
- Incapability to represent spatial dynamics - Due to its nature, it does not represent the spatial dynamics of a system, compromising what is possible to model (Melkonyan et al., 2020).
- Incorrect causality - Because of the simplicity of simulating causality in this modeling approach, if there is not a complex understanding of the system, researchers can end up modeling incorrect causality, leading to unreliable results. This is preventable by performing causality checks, evaluations, and causal relationship assessments (Mashaly and Fernald, 2020).

As described above, System Dynamics has a great capacity to represent systems, but certain elements or relationships are difficult to represent due to its nature. There is an interest in identifying other approaches and capabilities to represent space and modal split to achieve the desired solution.

2.2 Agent-Based Models

Given the complexity of transportation systems and travelers' unpredictable behavior and dynamic environment, researchers have been exploring Agent-based modeling approaches. This can be proven by the numerous recent articles and literature reviews in the area (Kagho et al., 2020), (Huang et al., 2022), (Delcea and Chirita, 2023), (Uthpala et al., 2023). Applications in transportation study areas include traffic control (Yu et al., 2021), (Xiong et al., 2018), (Xu et al., 2019), and exploring the complex traffic environment (Karaaslan et al., 2018). This section aims to explore the main principles and components of the modeling approach and the relevant models regarding urban mobility.

2.2.1 Context

Agent-based modeling does not have a clear beginning, unlike System Dynamics. It has connections to many other fields, including complexity science, systems science, System Dynamics, computer science, management science, the social sciences in general, and traditional modeling and simulation. The approach has historical roots in complex adaptive systems and the underlying notion that “systems are built from the ground-up,” in contrast to the top-down systems view taken by System Dynamics.

According to Bonabeau (2002), in agent-based modeling, a system is modeled as a collection of autonomous decision-making entities called agents. Agents interact with other agents, which in turn influences their behaviors and the system of which they are comprised. Reasoning the individual agent's decision and interactions with others in their environment leads to emergent macro-scale phenomena (Bonabeau, 2002). There are multiple perspectives on what an agent is. Macal and North (2005) present some principles for the practical characteristics of agents:

- An agent is identifiable, a discrete individual with a set of characteristics and rules governing its behaviors and decision-making capability
- An agent is situated, living in an environment with which it interacts with other agents.
- An agent is goal-directed, having goals to achieve (not necessarily objectives to maximize) concerning its behaviors.
- An agent is autonomous and self-directed.
- An agent is flexible, and has the ability to learn and adapt its behaviors over time based on experience.

There have been many applications of Agent-Based Modelling in different areas, for example simulating emergency evacuation processes (Delcea et al., 2020), (Ionescu et al., 2021), transportation sector (Diallo et al., 2023), (Levy et al., 2018), medicine (Badham et al., 2018), (Hunter and Kelleher, 2022), among many areas.

Lempert (2002) argues that Agent-Based models excel at relating the heterogeneous behavior of agents with different information, decision rules, and situations to the macro behavior of the overall system. The modeling approach's main strength is describing the behavior of inherently unpredictable systems. In policy-making, where these types of systems can be the case of study, Agent-based modeling can provide important insight that is not possible to get through traditional mathematical representations, such as System Dynamics.

2.2.2 Model Characteristics

This subsection explores Agent-Based approaches to represent mobility to understand how researchers model complex systems through this approach.

The simulation framework SimCo (Adelt et al., 2018) studies the governability of complex socio-technical systems experimentally by means of Agent-based modeling. The technological subsystem is composed of Nodes, Edges, Controls, and Technologies. Nodes define case-specific features. "Home Nodes" define where an agent typically starts, "task nodes" define places agents travel to in order to fulfill tasks, and "standard nodes" do not possess specific features but only serve as intermediate steps on long-distance journeys. Edges are the connections between nodes. Technologies are the modes of transportation chosen by the user, such as cars, bicycles, and public transport. Controls can affect nodes and edges, allowing restrictions on which technologies are allowed in each. Agents possess location, tasks to accomplish, and general preferences. In this paper, different kinds of agents are created based on their priorities: cheap, fast, eco-friendly, and comfortable. They choose the desired technology based on what is available for the task they need to fulfill and their own preferences, taking into account perceived costs and gains obtained by surveys rather than objective data. The agent sets are based on real-life surveys that depict the preferences of citizens. The setup in the experiment is based on realistic scenarios from typical mid-sized German towns. It is evaluated regarding CO₂ emissions, public transport usage, bicycle usage, and car usage.

Kii et al. (2021)'s goal is to study the impact of decentralization and rail network extension on future traffic. The authors use the land use model SILO (Moeckel, 2017) and the traffic assignment model MATSim (Horni et al., 2011) to represent the urban mobility from 2015 to 2050. Land use and transportation interact with each other in the long term, as the location of households and firms defines the origins and destinations of most trips, while congestion levels affect the location choice of households and firms. There is no big focus on validating the model, leaving verifying the certainty of the results obtained by this method to future work.

Fujii et al. (2017) explore constructing a new framework for simulating mixed traffic consisting of cars, trams, and pedestrians. They create a three-layered road network model based on a pre-existing multi-agent-based car-traffic simulator. They create car, tram and pedestrian agents and

perform extensive verification in different scenarios comparing with real-world data. Overall, the researchers conclude there is great potential for the proposed framework because it shows good agreement with the observed empirical values.

Urquhart et al. (2019) simulate the decisions that have a big impact on citizens' everyday mobility: the choices of transport to and from work. The agents use the BDI model to make decisions. The agents have access to the expected journey time and the feedback from other agents on previous congestion, which might impact their decision. In the case of walking, it is chosen that agents have a predisposition to make the choice to walk as it is viewed as being affected more by lifestyle than journey duration. The simulation results are compared to real data from surveys of Edinburgh Napier University, providing an interesting view of how to model commuter's choices so it matches the real data.

In the model described by Ahanchian et al. (2019), each agent represents a group of travelers with homogenous socio-economic characteristics, and the heterogeneity of travelers is defined by generating a population of agents to simulate that different groups of transport users have specific preferences. This is so policy makers can analyze the potential of imposing policies in different geographical zones, on specific groups of people, and for certain trip purposes in long-time horizon. The groups are based on the results from a recent survey. The simulation runs from 2010-2050, from 2016 on, the population is generated using a Monte Carlo simulation. The traveler's heterogeneity guarantees that agents have specific preferences when selecting a mode choice: private car, non-motorized transport and public transport. Each agent derives a utility for each alternative based on tangible costs and the value of travel time, and the traveler chooses the mode with the highest utility. The agent's choice of a certain transport mode influences the perceived congestion and waiting times. This is inspired by the "SimCo" framework explained above. The calibration and validation were done by comparing with The Danish Land Transport Model.

Motieyan and Mesgari (2018)'s the goal is to use Agent-based modeling to make optimum decisions in a region, leveling the indicators for Transit-Oriented Development and public transit infrastructure. Each neighborhood of the city of Tehran is modeled as an agent. The agents compute a number of land-use and transportation indicators based on appropriate models in GIS (Geospatial Information System). The authors define certain upstream policies, for example: "Adding residential land use", "Construction of a subway station", "Adding administrative land use", "Development of the current transit fleet and its service performance", etc, their predicted outcomes as utility functions and constraints needed to implement. Some policies require cooperation with other agents, and there are clear regional-level constraints. During the simulation, the agents interact directly to ensure the neighborhoods with stronger needs for change get the maximum benefit from the available policies. The only validation and statistical analysis performed is to compare the metrics before and after implementing the policies defined by Agent-Based modeling.

Manley et al. (2014)'s goal is to decrease computational cost while still maintaining a good representation of the overall system. They combine a macroscopic-level traffic dynamic model with agent-based modeling to describe the population to attempt to simulate driver behavior in

a detailed fashion at a highly scalable level. Drivers are modeled as agents that make complex autonomous decisions, while road segments are modeled as other agents that accept or not new drivers according to the traffic rules governing travel time and saturation. When a driver joins a road segment, it remains there until the expected departure time is reached, each time the traffic conditions on that road segment are recalculated. In congestion environments, agents cannot transition to the next roads, possibly forming a traffic queue. The model ensures the movement of potentially numerous individuals is encapsulated within a single road segment, reducing the number of operations required in each step. The approach is compared with a fully Agent-based simulation in a case study, resulting in minimal variation in on-the-road traffic patterns between the two approaches. As expected the purely agent-based approach has double the mean processing time. The model lacks a full validation process against available observed traffic data. The authors state this can be a useful framework for implementing detailed individual-level behavior within a large-scale urban simulation. They state there is ample room to explore other models of macroscopic traffic interaction.

Agent-based approaches allow more freedom to represent the relationships between the system's elements. There is a much larger focus on travelers' choices and behaviors, which comes naturally to the modeling approach. The spatial dimension also adds important information to the view of a mobility plan. Overall, it seems to have a great capability of representing the interactions and relationships existing in transportation systems.

2.2.3 Policy modelling

This section aims to explore how researchers choose to represent policies and the representation opportunities it provides when compared to System Dynamics.

This approach allows for modeling policy as concrete changes to the infrastructure. For example, [Kii et al. \(2021\)](#) study the effect of implementing the concrete metro lines the city has planned and how it affects agent's behaviors. Similarly, [Fujii et al. \(2017\)](#) simulate a possible tramway extension in great detail, how it affects the road infrastructure surrounding it, and through that, can clearly identify the predicted effects on traffic in that area. They also explore the impact of signal control on traffic in the area affected. By being able to model traffic behavior with detail, they then also get insight into how it affects travelers' behaviors and, with the new routes, predict the effect on other locations around the city.

It is also studied the implementation of certain policies that encourage or discourage the use of transportation modes, and their effect on the agent's behavior. For example, [Ahanchian et al. \(2019\)](#) defined multiple scenarios. Expanding public infrastructure meant increasing the trains and buses by 10%. Incentives for sustainable modes meant decreasing public transport ticket price by 20%, free parking for train users, and free recharging of electric bicycles. Disincentives for private cars meant increasing the fuel tax by 50%, increasing registration and annual ownership tax of a fossil fuel dependent vehicle by 50%, doubling the parking cost, and collecting toll on vehicles coming into the city. A combination of all the scenarios is also tested. [Adelt et al. \(2018\)](#) explore scenarios for lowering car usage in cities and observe how it affects agent's choices.

Three governance scenarios are tested: Soft control, where costs of agents using the car are raised stepwise if traffic jams occur or pollution exceeds limits; strong control, where there are full technology bans if certain limits are reached; and a mix of the two. [Kii et al. \(2021\)](#) do not explore these policies but suggest similar ones as future work, such as road pricing, park-and-ride, promotion of active travel modes, and travel demand management through education, reinforcing Agent-based capability to model these.

Another observed way of modeling policy was to change the represented location of residents and areas of interest to simulate polycentricity. [Fujii et al. \(2017\)](#) simulate 20% of the projected population moves to different predetermined locations. They compare these scenarios across time and without policy implementation, solely following the current trends. This way, they can explore how investing in the change of the city's organization would impact mobility.

For [Motieyan and Mesgari \(2018\)](#), the approach to study policy is different. The authors want to optimize the results of policy choice in a city. For this, they define each neighborhood as an agent, and each policy's predicted effect is calculated through utility functions. There is more focus on neighborhood communication to maximize joint benefit and reach an equilibrium. Through this, they directly ensure the neighborhoods with stronger needs for change get the maximum benefit from the available policies.

The ability to model spatial characteristics provides the capacity to model policies that are not as easily explored by System Dynamics approaches, such as understanding the true impact of transportation expansion to different areas and how people are projected to respond to it.

2.2.4 Current challenges and limitations

These are the current challenges of Agent-based Models found in the literature:

- Input data - It is stated that the data used has a great impact in the results produced. The possible errors, bias, uncertainty, and time variability of data and its effect on the results are not researched enough. ([Kagho et al., 2020](#))
- Cost of computation - The cost of computation of a simulation with a large number of agents remains a major drawback for this type of simulation, especially considering modeling large-scale transport networks consisting of a large number of entities. There is a lack of innovative approaches to tackle the issue. ([Kagho et al., 2020](#)), ([Huang et al., 2022](#))
- Transparency - There is a need to explore transparency through sensitivity analysis, mathematical descriptions of the different states of the model, description of model variability, and clear descriptions of parameter set-up and calibration.
- Validation - Different methods like comparing with analytical models should be explored to increase the credibility of the results of agent-based models. ([Kagho et al., 2020](#)), ([Huang et al., 2022](#))
- Reproducibility - Because there are no reporting standards for Agent-Based models, reproducibility is not ensured. ([Kagho et al., 2020](#))

- Standardization - There is a need for a properly defined body of knowledge to ensure there is a common language and definition of terms, clear standard procedures, analysis, and model expectations.(Kagho et al., 2020)
- Agent's behavior modeling - How to model complex and adaptive behavior remains challenging. Incorporating AI could provide more insights to improve the previous modeling. (Huang et al., 2022)

The approach provides good results and flexibility to represent real-world scenarios. Despite the presented limitations and challenges it is a promising approach to represent complex, unpredictable behaviors.

2.3 Hybrid Models

Hybrid Models have been proposed and discussed for a while, but recently, there has been a surge in implementation. This section aims to explore the main principles of the modeling approach and the context in which it is used, focusing on System Dynamics and Agent-Based implementations and their applicability in the context of urban mobility.

2.3.1 Context

Hybrid simulation is defined as the combination of two or more modeling approaches. According to Mustafee et al. (2017), most Hybrid Models end up being a combination of Discrete-Event Simulation, System Dynamics, and Agent-Based Modeling.

The main focus will be on combining System Dynamics and Agent-Based Modeling. There are clear differences between the approaches presented in Table 2.2 based on a table taken from Milling and Schieritz (2003).

Table 2.2: Comparison of System Dynamics and Agent-based Simulation (Milling and Schieritz, 2003).

	System Dynamics	Agent-based Simulation
Basic building block	Feedback loop	Agent
Unit of analysis	Structure	Rules
Perspective	Macro	Micro
Adaptation	Change of dominant structure	Change of structure
Handling of time	Continuous	Discrete
Mathematical formulation	Integral equations	Logic
Origin of Dynamics	Levels	Events

There is a lot of literature indicating what is the best approach. Despite the various differences, the two approaches have the same goal: the search for principles underlying the dynamics of complex systems. There are authors in support of the development of Hybrid Models (Vincenot

et al., 2011), (Swinerd, 2014). Ding et al. (2018) name three reasons why combining them would be valuable:

- System dynamics could be used to reflect the highest level of abstraction but be complemented by Agent-Based modeling in certain areas, depending on the nature of the elements to represent lower levels of abstraction.
- System Dynamics could be complemented with Agent-Based modeling capacity to include heterogeneous elements.
- Agent-based modeling has a much better capacity to represent complex systems with relatively simple rules

Hybrid modeling allows capturing the individual-level interactions represented by Agent-Based modeling and the aggregate-level behavior represented by System Dynamics to gain a more complete and comprehensive understanding of complex systems (Nguyen et al., 2024), (Mykoniatis and Angelopoulou, 2020), (Lättilä et al., 2010). The approach allows for a "holistic view" which is essential to guarantee an accurate representation of real-world systems.

There is growing interest in this area (Tako et al., 2019), (Nguyen et al., 2024), (Mykoniatis and Angelopoulou, 2020), (Zhang et al., 2019) and practical examples in different fields: operational research (Brailsford et al., 2019), cyber-physical systems (Tolk et al., 2018), health care (Kar et al., 2022). Jonh Sterman expressed an interest in using different methods under System Dynamics principles when discussing the approach's path forward: "System dynamics models can be implemented using a wide range of methods, including differential equations, difference equations or discrete event simulation; aggregated or disaggregated compartment models or individual-based models; deterministic or stochastic models; and so on." (Sterman, 2018)

Despite this, there is a small number of models representing urban mobility or transportation systems in the literature. Therefore, this section will be structured differently, focusing more on conceptual approaches and examples.

2.3.2 Motivations for the application of Hybrid System Dynamics and Agent-based models

Nguyen et al. (2024) identified the contexts where using Hybrid Modeling instead of a traditional approach is relevant. Some of these will be explored to understand the category the problem at hand would fit into, and the benefits of each approach will be compared.

The approach has been used to analyze different policies in systems with extensive and specific operational/local circumstances. Even though this problem is usually modeled through System Dynamics, the authors consider that a hybrid approach through dynamically switching between System Dynamics and Agent-based modeling could provide different, interesting insights. It could provide a macro view of the system and the impacts of agent behavior at the micro level, and it could offer greater flexibility to model different operational circumstances or intervention scenarios explicitly, providing insight into why a strategic policy might not work in the problem

represented. [Mazhari et al. \(2009\)](#) presents a practical example of this situation. Given that this dissertation aims to model policies in urban mobility, a complex system with various causal relationships, this approach could be valuable in identifying previously unstudied interdependencies.

Another identified context where this approach is useful is to model systems involving interdisciplinary processes or organizational factors. In the literature, these problems are typically modeled both through System Dynamics and Agent-Based models. Perhaps combining them and using different approaches to model different subsystems could provide a clearer, more effective representation. The combination would allow no compromise in the representation of disciplines and subsystems. It also tackles the trade-off between the computational and the predictive performance of the model. [Kolominsky-Rabas et al. \(2015\)](#) present a practical example. To fully evaluate the impact of certain policies in the overall city, the proposed model needs to represent different disciplines of different natures: economy, emissions, energy efficiency, congestion, mobility, etc. Given the interdisciplinary of the problem at hand, this approach could fit the modeling requirements.

The last relevant identified context regards systems composed of entities that interact socially or spatially, affecting and being affected by a dynamic global environment. This case is typically modeled using Agent-Based approaches. Still, the authors consider the rich representation of the external environment could provide new opportunities to understand the relationships between agents' behaviors and the external environment. They consider that a dynamic urban environment where a spatial, social structure of agents live, is characterized by causal relationships, and these would not be properly represented through System Dynamics. Joining the approaches allows for a better representation of the problem at hand. The practical example regards the social-spatial fragmentation and segregation affected by cause-effect chains of urban shrinkage ([Haase et al., 2012](#)). The nature of the problem studied in this dissertation consists of modeling and evaluating the effects of concrete changes in the dynamic global environment. The transportation system could be modeled through Agent-Based modeling, and all the target components that affect and are affected by it could be modeled through System Dynamics. There is a clear match between the context identified and the problem at hand, suggesting that Hybrid Modeling is an appropriate approach to represent urban mobility plans.

The problem at hand has characteristics similar to all the described contexts above. The approach that seems to capture the desired aspects of the target problem is to represent agents in a dynamic environment represented by a System Dynamics model. It could expand the notion of policy effect on the agent's behaviors and capture the feedback loops that define a city and how populations change across the years. The limitations, consequences, and lack of examples in implementing this approach to similar problems in the literature still need to be explored thoroughly.

2.3.3 Hybrid Models design categories

[Swinerd and McNaught \(2012\)](#) proposed three different design categories for hybrid models: Integrated, Interfaced, and Sequential.

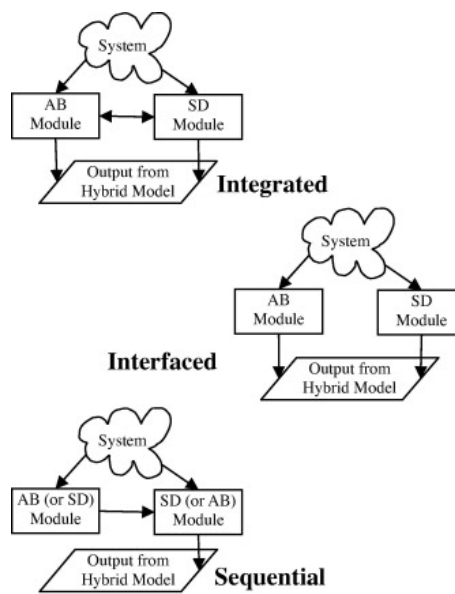


Figure 2.3: The proposed three classes of hybrid AB–SD simulation (Lewe et al., 2014).

Integrated refers to using different simulation paradigms within the same model architecture. Examples are Gaube et al. (2009) and Schieritz and Grobler (2003). Gaube et al. (2009) created a model to represent coupled socio-ecological systems in land-change science for a defined region of Austria. This model contains three models of different natures: one agent-based, one based on system dynamics principles, and the other a spatially explicit land use module. The outputs of each model directly affect the other ones. Schieritz and Grobler (2003) create a hybrid simulation model designed for supply chains. This model incorporates System Dynamics models to portray decision-making processes within individual companies while employing Agent-Based modeling to represent the connections between companies in the supply chain. They complement the System Dynamics approach to increase flexibility and make it possible to represent supply chain connectivity as a function of time.

The authors classify models as interfaced when they alternate between Agent-based models and Systems Dynamics; they run in parallel, and their outputs are combined as required to represent the desired output as a function of time.

A sequential design is when one modeling technique is used to inform the design, use, or starting conditions of another. An example of this is the model created by Lewe et al. (2014), where a pre-existing Agent-based model is used to calibrate and inspire the correlations in a System Dynamics model.

2.3.4 Practical Examples

As previously explained, no examples in the literature were found for the evaluation of policies in urban mobility using specifically System Dynamics and Agent-Based modeling. With that in mind, this section explores the relevant work identified.

Lewe et al. (2014) developed a model regarding mobility and transportation systems. They state that both micro- and macro-level views are essential for complex systems research. They aim to provide a holistic view of a system modeling intercity transportation. The authors develop a System Dynamics model where the subsystem representing mode choice having as output demand for each transportation mode is inspired and calibrated against a pre-existing and calibrated Agent-Based model (Lewe et al., 2011). This model inspires the design of the subsystem, and multiple sensitivity analyses are done to guarantee it can capture the behavior displayed in the Agent-Based model. A “confidence box” is defined, within which future values are expected to remain through cross-calibration. The researchers state they have good results, creating a faster surrogate version of the Agent-Based model to forecast the multi-modal transportation demand. They suggest the same approach can be applied to different application areas and suggest further investigation linking transportation fleet and emissions models to assess environmental impacts. Assaad et al. (2020) developed what they call a System-of-Systems Model with the goal of simulating emergent traffic behavior integrated into a larger view of an evolving system. The model they developed is a hybrid approach that includes: logistic model, system dynamics, stochastic cellular automata, chaos theory, and Lotka-Volterra model. They model different subsystems: population and GDP, Carbon dioxide emission, gasoline price and total vehicle trips, traffic demand, public and private transportation, transportation investment, and traffic congestion with different modeling approaches, achieving good results. They modeled the transportation network as a dynamic system of systems rather than as a static model.

In a different domain, Wang et al. (2019) developed a hybrid simulation model that combines Agent-Based simulation and System Dynamics to study multilateral bidding in electricity markets. They use System Dynamics principles to simulate the complex electricity market system and different types of agents with different priorities to simulate bidding with different strategies. They conclude that the approaches complement each other, achieving a representation that would not be possible with only one. They present an example of System Dynamics to represent a dynamic global environment and agents interacting based on it.

2.3.5 Tools

The goal of this section is to explore the available tools that have been used in the literature to study Hybrid Modeling.

There is a consensus in the literature about using AnyLogic for hybrid modeling (Brailsford et al., 2019), (Mykoniatis and Angelopoulou, 2020), (Liu et al., 2018), (Langarudi et al., 2021), (Nguyen et al., 2024), (Osgood, 2007). This commercial software allows modelers to use Agent-based approaches, System Dynamics, and discrete event simulation simultaneously. Even recognizing this, certain authors have criticisms, Liu et al. (2018) claim AnyLogic has limitations in accounting for different types of agent decision-making processes associated with optimizations in a hybrid model with multistage uncertainty, and Langarudi et al. (2021) state that the clear limitations of this model highlights the challenges associated with hybrid modeling due it not being a

very developed and studied approach. This tool provides industry-specific libraries, such as pedestrian flows and simulation of road traffic, and GIS map integration, which is relevant in the context of the problem. According to its [website](#) it is used and trusted by multiple large organizations, for example, Intel, PWC, Deloitte etc.. It has active communities in LinkedIn, StackOverflow and ResearchGate, with multiple posts per day, as of the time of writing.

Other platforms for hybrid cross-paradigm modeling exist, such as Nova ([Salter, 2013](#)), GAMA ([Grignard et al., 2013](#)), and Netlogo ([Wilensky and Rand, 2015](#)), but they are not as used in the explored literature reviews, nor recommended by researchers. In the literature, there are examples of models created using only System Dynamics tools. This usually involves the use of arrays to be able to cope with added complexity ([BenDor et al., 2009](#)), ([Akkermans, 2001](#)).

The Python Library PySD ([Martin-Martinez et al., 2022](#)) consists of a tool that turns VENSIM and STELLA implementations of System Dynamics models into Python modules, adding features such as the ability to incorporate with other simulation methods. It was intended to provide the ability to integrate System Dynamics models with Big Data and Machine Learning. There is already System Dynamics software that provides easy-to-use interfaces, meaning that it is accessible to people who do not have programming skills. PySD can be a great tool, given the freedom of implementation for a possible method to be integrated into System Dynamics. It allows for both easy design of the System Dynamics models and freedom for integration with more complex methods.

2.3.6 Current challenges and limitations

These are some of the current challenges of Hybrid Modeling with Agent-Based Methods and System Dynamics:

- Limited methodological frameworks - [Nguyen et al. \(2024\)](#) describe many examples in the literature as “ad hoc and pragmatic with no clear methodology”. This observation is shared by [Brailsford et al. \(2019\)](#).
- Over complicate representations - [Brailsford et al. \(2019\)](#) fear the risk that the use of Hybrid modeling approaches may make simple problems more complicated.
- Lack of reproducibility - much of the existing work does not include clear documentation of the modeling process, making it difficult to reconstruct presented models ([Brailsford et al., 2019](#)), ([Nguyen et al., 2024](#)).
- Limited easy-to-use tools - there is a growing need for tools that allow for easy integration of modeling approaches ([Łatuszyńska, 2020](#)).

There are still very few studies on integrating System Dynamics and Agent-Based models ([Łatuszyńska, 2020](#)), which is why most of the presented limitations exist. While this can mean increased difficulty, it can also mean research opportunity, given the demonstrated interest by researchers.

2.4 State of Practice

It is relevant to explore the current state of design and evaluation of Urban Mobility Plans to ensure the development of relevant tools. As a part of the European Green Deal and the Sustainable and Smart Mobility Strategy, the EU has been focusing on aligning European guidelines and priorities with key concepts focused on transportation and urban mobility. This section will focus on the main topics being explored at the European and National levels.

2.4.1 Sustainable Urban Mobility Plans (SUMP)

Sustainable urban mobility planning, or SUMP, was first introduced in the 2013 Urban Mobility Package by the European Commission. Specifically, their goals include: providing all citizens with mobility options that enable access to destinations and services; enhancing road safety; minimizing air and noise pollution, greenhouse gas (GHG) emissions, and energy consumption; increasing the efficiency and cost-effectiveness of transporting people and goods; and boosting the appeal and quality of the urban environment and urban design to benefit citizens, the economy, and society as a whole (Instituto da Mobilidade e dos Transportes, 2023b).

According to Rupperecht et al. (2020) "A Sustainable Urban Mobility Plan is a strategic plan designed to satisfy the mobility needs of people and businesses in cities and their surroundings for a better quality of life. It builds on existing planning practices and takes due consideration of integration, participation, and evaluation principles." It consists of a long-term planning framework involving all relevant parties in the planning and monitoring of cities' urban mobility. It focuses on the involvement of multiple stakeholders to achieve clear long-term commitment and widely agreed-upon goals to boost effectiveness in policy making. Sustainable Urban Mobility Planning is based on eight principles:

- Plan for sustainable mobility in the "functional urban area"
- Cooperate across institutional boundaries
- Involve citizens and stakeholders
- Assess current and future performance
- Define a long-term vision and a clear implementation plan
- Develop all transport modes in an integrated manner
- Arrange for monitoring and evaluation
- Assure quality

The SUMP documentation enumerates the principles and overall approach to creating a sustainable mobility plan. There are clear and documented suggested phases with goals and desired outputs:



Figure 2.4: The 12 Steps of Sustainable Urban Mobility Planning (Rupprecht et al., 2020).

- Preparation and analysis
- Strategy development
- Measure planning
- Implementation and monitoring

These are illustrated and further explained in Figure 2.4, taken from Rupprecht et al. (2020).

Since then, the concept has been recently updated in 2023, integrating new EU strategies and policy priorities without major changes to its original philosophy. Over the past decade, the Commission has promoted the concept, which is widely used by many cities across the EU on a voluntary basis for planning their transition to attractive, inclusive, and sustainable urban mobility (Council of the European Union, 2023). Examples are Milan Italy, where the number of residents using cars is already down to 50%, well below the Italian average (Council of the European Union, 2023), Warsaw Poland which has seen road accidents decreased by 21% and road deaths by 60% (Kalenkiewicz and Bisak, 2017), and Tartu, Estonia, which managed to double the modal share of cycling from 4% to 8% in just five years (Tartu Linnavalitsus, 2018). In March 2023, the Commission called on each Member State to implement a national program with a dedicated office to help cities with sustainable urban mobility planning (Council of the European Union, 2023).

As it has been shown, there is a clear effort to implement this framework within EU cities. In Portugal it is mandatory for Municipalities, Intermunicipal Communities, Metropolitan Areas, and

Functional Urban Centers to develop a Sustainable Urban Mobility Plan or PMUS according to the Climate Framework Law (Law No. 98/2021, of December 31) in the domain of mobility and transport, Article 47, paragraph 4 (Instituto da Mobilidade e dos Transportes, 2023b). A priority is set for metropolitan areas and municipalities with more than 100,000 inhabitants in the context of the TEN-T policy. This includes the city being studied in the context of this dissertation, Gondomar, and many other Portuguese cities. Despite this, according to Instituto da Mobilidade e dos Transportes (2023a), only 61% of the Portuguese entities enquired declared to have resources of planning allocated to urban mobility. This demonstrates a clear lack of comprehensive planning and resource allocation dedicated to urban mobility in Portugal. This disparity highlights significant challenges that Portuguese municipalities and metropolitan areas face in effectively developing and implementing their Sustainable Urban Mobility Plans. Moreover, the effectiveness of these plans heavily relies on the cooperation and coordination among different levels of government and stakeholders, including local communities, businesses, and public transport providers. For cities like Gondomar, this means fostering a collaborative approach to urban mobility that considers local needs and leverages available resources efficiently.

2.4.2 Simulation tools in the context of SUMP

Transport models are essential tools in the Sustainable Urban Mobility Plan (SUMP) process, providing reliable and consistent input across various planning stages. They are particularly valuable during scenario development, measure appraisal, selection, and monitoring phases. By predicting the impacts of different policy and measure combinations, these models consider complex interactions and potential reinforcing or rebound effects, helping to identify the most effective integrated strategies. Beyond establishing a baseline scenario, transport models facilitate continuous monitoring of the transport system, ensuring that implementation stays on track and allowing for timely adjustments as needed (Rupprecht et al., 2020).

Given the SUMP principle of multiple stakeholder collaboration, it is important that everyone involved has a clear view of the state of the mobility system and the policy's impact. It is advantageous that the discussion is based on quantitative, transparent data and not only perceptions and opinions. Simulation tools can provide this, making them a valuable asset in decision spaces.

According to Rupprecht et al. (2020), aggregate models, in particular, can be very useful for initial policy screening within the SUMP process. They can be useful in exploring different sustainable policy measures and quantifying their impacts within a consistent framework. They claim that different model types can be used in different situations, and policies should be further tested through more detailed modeling approaches. Still, aggregate modeling can provide a view of the system and set up implementation pathways for future scenarios.

2.4.3 Key Indicators

During the development of this dissertation, the indicators were updated to account for the EU's trans-European transport network policy, the TEN-T policy, aiming to connect key points across

the EU. At this point in time, the Urban Mobility Indicators (UMI) are still being developed by the European Commission to account for sustainability, safety, and accessibility. There is a focus on the following areas:

- Greenhouse Gas emissions
- Congestion
- Deaths and serious injuries caused by road crashes
- Access to mobility services
- Air and noise pollution in cities

The current focus is on collecting data for the key European nodes for the EU transportation network, which includes the city of Gondomar being studied. Even though this information was published after the development of the project it is still important to showcase the priorities being set and how the tool developed contributes.

Given the changing indications, this dissertation focused on two documents. The Technical support related to sustainable urban mobility indicators (European Commission, 2020) outlines a set of indicators designed to measure the sustainability and performance of urban transportation systems. The guidelines aim to ensure consistency in data collection and analysis, facilitating comparability between different urban areas. Key areas covered include environmental impact, accessibility, safety, and quality of service. The document serves as a comprehensive reference for policymakers, urban planners, and researchers involved in the assessment and improvement of urban mobility. The main issue is that it does not provide clear formulas for calculating each indicator. This information is key given the lack of experience in transportation research, terms, and concepts. The "Technical support related to sustainable urban mobility indicators" (European Commission, 2020) document was inspired by the indicators described by the "SMP2.0 Sustainable Mobility Indicators" published by World Business Council for Sustainable Development (2015).

The "SMP2.0 Sustainable Mobility Indicators" document follows the principles required in SUMP and provides clear and straightforward guidelines on the goals and detailed instructions on calculating each indicator. Table 2.3 presents the indicators available and their dimension regarding the area of impact. Different indicators require different data. Some of them could not be represented in a model because it regards public opinion obtained via surveys. There was an examination through the list and data required to understand what made and did not make sense to include in the final model.

Table 2.3: Overview of Sustainable Urban Mobility Indicators (World Business Council for Sustainable Development, 2015)

Indicator	Type	Area
Affordability of public transport for the poorest people	Main	Quality of life
Accessibility for mobility impaired groups	Main	Quality of life
Air polluting emissions	Main	Quality of life
Noise hindrance	Main	Quality of life
Fatalities	Main	Quality of life
Access to mobility services	Main	Quality of life
Quality of public area	Main	Quality of life
Urban functional diversity	Main	Economic success
Commuting travel time	Main	Economic success
Economic Opportunity	Main	Economic success
Net public finance	Main	Economic success
Mobility space usage	Main	Global environment, Economic success
Emissions of greenhouse gases (GHG)	Main	Global environment
Congestion and delays	Main	Mobility system performance
Energy efficiency	Main	Global environment, Mobility system performance
Opportunity for active mobility	Main	Global environment
Intermodal integration	Main	Mobility system performance
Comfort and pleasure	Main	Quality of life, Mobility system performance
Security	Main	Quality of life, Mobility system performance
Occupancy rate	Additional	Global environment
Motorization rate (4W, 2W)	Additional	Global environment
Modal split	Additional	Mobility system performance
Smartphone penetration	Additional	Mobility system performance
Vehicle miles travelled per capita	Additional	Global environment
Speed in the transport network	Additional	Economic success, Mobility system performance
Car friendliness of the city center	Additional	Mobility system performance
Availability of public transport cards	Additional	Mobility system performance

2.5 Conclusions

The goal is to both provide a tool that is useful in real-case scenarios and contribute to the research surrounding modeling approaches. In this context, it is important to understand policymakers' current necessities and priorities to create a tool that can be used in real-life scenarios. It is a priority in the context of the entire EU, but more specifically Portugal, to have the necessary tools to approach the mobility necessities of its Municipalities.

In the context of System Dynamics models, an aggregate modeling method, there must be a focus on providing an overview of the main dimensions targeted on Sustainable Urban Mobility Plans, namely Modal Share, Congestion, Greenhouse Gas Emissions, Road Safety, etc., and how they are impacted by the other subsystems that represent the city as a complex environment. It can be an aid in the strategy development phase of the Sustainable Urban Mobility Plan, providing a view of the citizen's behaviors and responses, especially in cases where there has been less focus on mobility, so there is not as much data to feed highly specific models.

While System Dynamics can capture well policies' effects through "what-if" scenarios and the effects across different areas because they only deal with non-spatial or highly aggregated spatial compartments (Wallentin and Neuwirth, 2017), it limits the type of policies that can be tested. It is not as capable of representing emergence due to the fixed nature of system structures. Agent-based models, on the other hand, provide new possibilities when representing policies and heterogenous behavior (Ding et al., 2018). Other approaches, such as spatial dynamic modeling and cellular automata, were briefly explored but did not seem as relevant. Combining Agent-based modeling and System Dynamics is growing in interest and provides an interesting approach given the need to represent multiple areas: sustainability, economic aspects of the city, mobility etc. There is interest in representing systems through System Dynamics principles but incorporating other approaches. This was even expressed by Jonh Sterman, an already mentioned very relevant figure in System Dynamics (Sterman, 2018) when discussing where the field should be headed. Given the lack of research found in the literature addressing hybrid modeling approaches to evaluate policies in urban mobility, it is an opportunity to explore its viability. The main research questions proposed are:

- How can System Dynamics and Agent-Based modeling interact in a hybrid approach to represent mobility?

An approach where the main components of the city and indicators are modeled through System Dynamics, including the main feedback loops, combined with a modal choice based on a disaggregated Agent-Based approach can be developed, runs within a reasonable time, and can be used in the typical use cases associated with System Dynamics models.

- Does the approach improve the traditional evaluation of policy of System Dynamics?

The integration of an Agent-Based modal choice allows for a new way to evaluate the effects of policy; this includes having a notion of relationship with space and evaluating how policy impacts different groups of people.

In summary, the goal is to create a tool based on System Dynamics principles, integrating an Agent-based submodel, that provides relevant indicators that are aligned with the principles described and how they change given common policies applied in urban mobility.

Chapter 3

Methodological approach

This chapter previews how to tackle the problem. The solution will be created with the multi-paradigm modeling framework (MPMF) defined by [Mykoniatis and Angelopoulou \(2020\)](#) as a guide. The chapter will be structured considering the framework's phases, with the description and overall objectives. A conceptual model will be developed respecting each modeling approach's principles and how they best interact with each other based on the literature review. In the following section, there will be a detailed exploration of the indicators available to make sure the model created fits the relevant point explored in the State of Practice. Based on that, in the following section there is a reflection on the best implementation pipeline that fits the requirements identified.

3.1 Overview of the Multi-paradigm Modeling Framework

The MPMF modeling framework's goal is to provide guidance on how to combine more than two simulation paradigms to form hybrid models. It focuses on joining Discrete Event, System Dynamics, and Agent-Based modeling. Even though this thesis aims to study Hybrid Modeling techniques involving Agent-Based Models and System Dynamics, this was the most complete framework found, and when defining the concrete objectives of the task at hand the exact models used will be defined. The methodology integrates the general steps for a single method implementation, adding steps for deciding and evaluating how to represent the system from a multi-paradigm point of view. The activities are described in Figure 3.1, taken from [Mykoniatis and Angelopoulou \(2020\)](#).

The framework is composed of 4 phases, as illustrated in Figure 3.2, taken from [Mykoniatis and Angelopoulou \(2020\)](#): Phase 1 includes the conceptual modeling steps, the goal is to define the problem, the objectives and the modeling approaches being used when, Phase 2 is the development process of the actual MPM model construction, Phase 3 consists of the verification and validation process and finally Phase 4 includes the report and documentation of the obtained results.

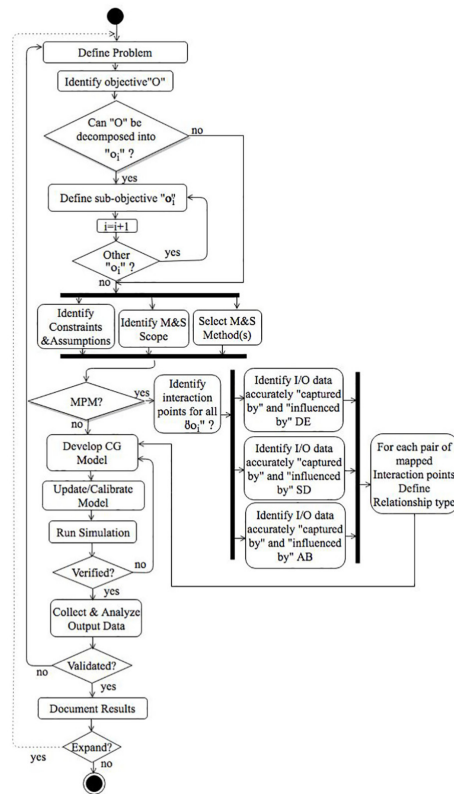


Figure 3.1: Activity diagram of internal view of MPMF (Mykoniatis and Angelopoulou, 2020).

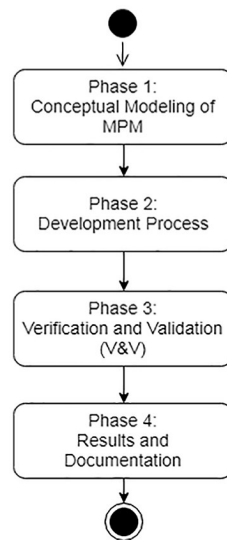


Figure 3.2: High-level view of MPMF framework (Mykoniatis and Angelopoulou, 2020).

The activities proposed in Phase 1 are the following:

- Define the problem
- Identify objective “O” and decompose them into sub-objectives “oi”

- Identify constraints and assumptions
- Identify M&S scope
- Selection of M&S method(s)
- Identify interaction points
- For each pair of mapped interaction points define the relationship type

The authors state that identifying the model scope is essential to provide good and clear results. It should be divided into sub-activities with clear desired results. These consist of defining the following:

- Defining content and form of results - meaning what is the desired form of output of the model.
- Defining boundaries - the goal is to define the beginning, ending, upper, and lower boundaries, meaning what are the inputs and outputs before, during, and after the simulation.
- Defining the level of detail - meaning the desired output precision, taking into account the added complexity.
- Defining degree of accuracy - meaning the validity of data being employed. In this phase, all the input data is collected, prepared, and validated.
- Defining the type of experimentation - meaning the type of analysis that will be conducted.

To address the selection of methods in a clear, methodical way there is an algorithm proposed. A set of criteria characterizes each model regarding Scope level, Required resolution, Abstraction level, Object, time etc. For each sub-objective selected, the user assigns a weight for the capability of representation of each model in each criterion. In the end, all the weights are ranked, selecting which method better represents each sub-objective. In [Mykoniatis and Angelopoulou \(2020\)](#) is the further formalization and exploration of the algorithm. The output should be a modeling approach adequate to each sub-objective.

The interaction points are the variables within each sub-objective that exchange of data between different models. To better represent the system each pair of variables that represent interaction points is assigned a relationship type. These can be:

- Direct replacement of values of variables - meaning variables representing the same attribute in both models.
- Aggregation/disaggregation - information exchange that needs to be aggregated or disaggregated from one model to the equivalent values of the other model.
- Causal relationships - meaning interaction points that are described by mathematical equations.

- Add/Remove/Inject/Transfer agents or entities.
- Control flow relationships - meaning “if”, “for”, and “while” statements that define the flow of a particular logic.
- Trigger Event relationships - meaning events such as timeout, message, condition, rate, and arrival.
- State-chart control - meaning a state that may control the flow among two models, update variables from other models, or trigger any other type of relationship.

These activities can help build a clear conceptual model, allowing for a smoother implementation. The following phases, Implementation, Validation, and Discussion of Results, are more straightforward and not highly defined by the framework proposed by [Mykoniatis and Angelopoulou \(2020\)](#).

Given the reported limitations of the Hybrid Models identified in the subsection 2.3.6, this dissertation will follow the methodological framework described. The goal is to provide clear documentation and justifications for the choices made. This will tackle the "lack of reproducibility" exposed during the literature review.

3.2 Conceptual Modeling

This section will present the conceptual model through the framework described above. The section aims to provide a clear explanation behind decisions made during the conceptualization of the hybrid approach.

3.2.1 Define the problem

The goal is to create a system based on the principles of System Dynamics that can represent mobility plans and test different policies regarding transportation. The model must be able to provide some of the most common indicators that represent EU principles. It should explore the mix of different modeling approaches to ensure different policies can be explored. More specifically, a policymaker should be able to characterize the city to study through the variables provided, obtain indicators that accurately describe reality, and provide projections for the evolution of those variables. There must be policies presented that the policymaker can explore and compare expected results between them. There must be a focus on how these impact citizens behaviors when choosing a mode of transport, highlighting the trend in policy that prioritizes mass transportation in urban centers.

3.2.2 Identify objective O and decompose them into sub-objectives o

The main objective has been described. It is to provide a system that encompasses the main aspects of what involves a mobility plan. In regard to indicators there is a priority set for Greenhouse gases,

since the main focus of the EU course of action is to achieve the European Green Deal objectives which include no net emissions of greenhouse gases by 2050 (European Commission, 2024). It is relevant that the model can then be integrated with further subsystems that aim to represent the necessary dimensions to calculate target indicators.

- O_1 - Describe the evolution of a population in the city, their purchasing power, and mobility needs.
- O_2 - Describe the infrastructure present and provide ways to change the conditions described.
- O_3 - Have a complex modal choice that responds to changes in the infrastructure, has some spatial characteristics, and integrates with the rest of the system.
- O_4 - Represent Greenhouse Gas emissions and how they might change given different conditions.

3.2.3 Identify constraints and assumptions

While the main assumptions and constraints are presented here, in each subsection describing the model, more assumptions are presented.

- Each trip is made through just one transport mode.
- People's purchasing power is accurately defined through income percentiles.
- Mobility conditions can be described by the area of road, cost per km to ride a car, the number of bus lines, bus trips, railway lines, railway trips, and ticket costs.
- Defining trips through matrices of Origin Destination pairs, regarding zones and not specific roads, can accurately describe citizens' mobility behaviors.
- There is credible data to support the model.

3.2.4 Identify M&S scope

The user can experiment with the model's 'what-if' scenarios and compare results. Because modal choice was identified as relevant when testing policies' results, there is a focus on expanding on previously described modal choice approaches while guaranteeing that it does not become computationally expensive since it was identified as one of the Agent-based models' limitations. For each experiment, key indicators inspired by the guidelines for urban mobility plans from the European Union will be presented, focusing on representing modal choice shifting results and their impact on the system. The effort to represent complex systems through simple relationships will be emphasized.

3.2.5 Selection of M&S methods

To select which simulation approach would be used to represent each sub-objective, the algorithm proposed by Mykoniatis and Angelopoulou (2020) was used. The algorithm is represented in Figure 3.3. The criteria selected were scope, situation, system process, modeling approach, object, and control time. Each criterion may be satisfied by up to three relevant variables of interest. The algorithm consists of assigning a value of interest to each criterion for each sub-objective. A weight is then applied to each choice, reflecting the importance of the corresponding criterion, where 0 represents the lowest importance, and 10 represents the highest. In the end, the approach chosen for each sub-objective is the one with the highest sum of weights, as displayed in Figure 3.3.

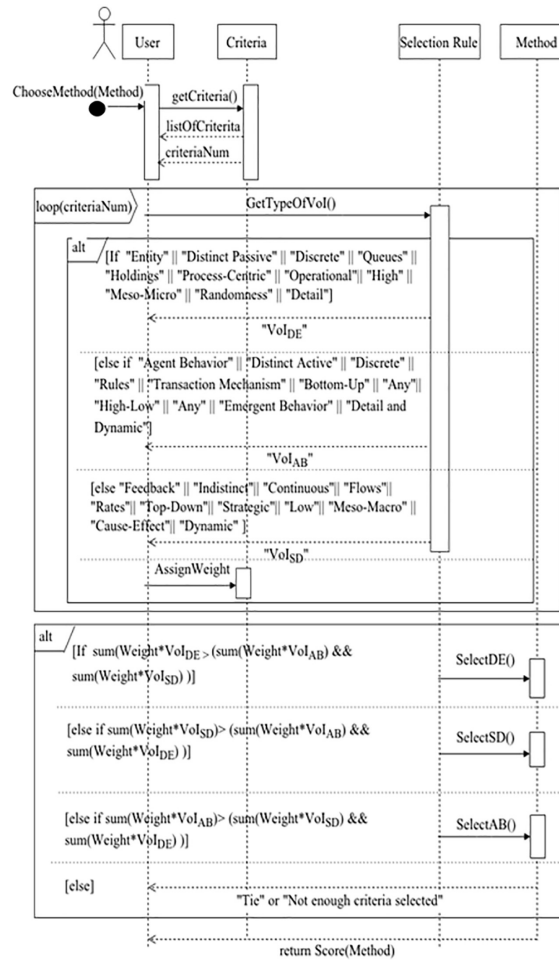


Figure 3.3: Selection of M&S method (Mykoniatis and Angelopoulou, 2020).

Based on the literature review, it was concluded that to simulate the heterogeneous behavior of a population and their choices, Agent-based models were appropriate. Since modal choice consists of how a population reacts to the concrete conditions available, it was considered a match with the bottom-up, Agent-based approach. On the other hand, broader aspects of the model, such as business growth, population increase, income growth, and the impact of emissions, are

more effectively represented using a top-down approach. These factors can be intuitively captured through aggregate relationships between variables, avoiding unnecessary complexity that might arise from modeling them as direct consequences of individual behavior. The choices documented in Table 3.1 for the best approach for each sub-objective are made under these assumptions.

Table 3.1: Analysis of choice of modeling approach for each o_i , adapted from (Mykoniatis and Angelopoulou, 2020).

Criteria	Value of Interest	Selection for o_1	w_1	Selection for o_2	w_2	Selection for o_3	w_3	Selection for o_4	w_4
Scope	Operational					X	2		
	Strategic	X	8	X	5			X	5
	Any								
Situation	Queues								
	Flows	X	7					X	5
	Rules			X	2	X	4		
System process	Discrete								
	Continuous	X	9	X	7			X	6
	Discrete/Continuous					X	3		
Modeling approach	Process centric								
	Top-down	X	5	X	8			X	3
	Bottom-up					X	10		
Object	Entity								
	Feedback	X	7	X	2			X	3
	Agent					X	10		
Control	Holdings								
	Stocks	X	9	X	10			X	5
	Transition mechanisms					X	2		
Time	Discrete								
	Continuous	X	9	X	8	X	2	X	9

The end result was to model all the dimensions of the system through System Dynamics, but the modal choice will be represented through Agent-Based modeling. There will be no representation of roads to address one of the identified limitations of the Agent-based approaches, which is being computationally expensive. Agents will make choices based on pre-made matrices describing the costs of traveling between zones through each transportation mode. While there is a loss in the details present in the simulation, it is identified as an essential trade-off to guarantee a smooth integration with traditional use cases of System Dynamics. These models typically represent long-term simulations and require a modal choice model that can be implemented accurately and run relatively quickly. This allows the modal choice model to be executed at each simulation step, ensuring a constant and responsive adaptation to changes in the system.

3.2.6 Interaction Points

Since the goal is to have a descriptive view of the system through System Dynamics while incorporating agents in the modal choice process, the interactions between the approaches will mostly surround the simulation of the population and infrastructure, how it changes, and the resulting impacts.

To describe the interaction, there will be more focus on a general view of concepts and how they correspond to the different modeling approaches than focus on specific variables. The exact variables will be described when presenting the Hybrid Model. With the definitions inspired by [Mykoniatis and Angelopoulou \(2020\)](#), the interactions can be described through the following:

- Population (SD) - Population (AB) - A.2 Disaggregation. While in System Dynamics, the Population is described through the number of people and socioeconomic conditions through income levels, in the Agent-based module, these are translated through the simulation of a Population of agents that represent the characteristics described. Aggregate information is translated to a disaggregate view.
- Infrastructure (SD) - Infrastructure (AB) - A.1 Direct replacement. The infrastructure and mobility conditions in the system must be translated to expected travel times and costs so agents can make decisions. The goal is that each change can directly translate to the system agents interact with.
- Agent's modal choice (AB) - Number of trips (SD) - A.2 Aggregation. The resulting agent's choices need to be aggregated to represent each mode's significance, meaning if the policies implemented affected the citizen's modal choice and, with that, impacted emissions and target indicators.

3.3 Target Indicators

Since this dissertation aims to provide a tool that can be used to test mobility plans to European standards, there is a focus on exploring the level of representation these indicators require and

which ones can be implemented, taking into account the restrictions remarked on the conceptual model. This section explores the indicators available that were chosen, taking into account the main goals of the system. The model was designed around these target indicators to guarantee usability in real-case scenarios.

The selection started by analyzing the indicators available and reflecting on which ones can be represented in the model being created, taking into account the restrictions previously set, and also represent an important indicator taking into account the current priorities set by EU standards and the stakeholders of the model. Table 3.2 enumerates the indicators made available by **World Business Council for Sustainable Development (2015)** and presents which indicators are considered possible to represent adequately in the model. Some of the formulas in the original document are based on population surveys; these are not adequately possible to represent in the developed model. The decision on the indicators to be represented was made with aid from stakeholders. Further information on the reasoning behind the decision for each indicator is available in the column "Reason for Decision"

Table 3.2: Overview of Sustainable Urban Mobility Indicators and their possible representation in the model being developed.

Indicator	Possible representation	Reason for Decision
Affordability of public transport for the poorest group	Yes	There will be a representation of income and ticket cost
Accessibility for mobility impaired groups	No	It is based on surveys
Air polluting emissions	Yes	It is relevant and there is representation of vehicle travelled miles
Noise hindrance	No	There is no data available for the case studied and it is not a priority
Fatalities	Yes	Possible statistical inference based on vehicles in the road
Access to mobility services	Yes	Essential to represent citizen's mobility
Quality of public area	No	Based on surveys
Urban functional diversity	No	It needs more detailed spacial representation
Commuting travel time	Yes	Relevant taking into account the goals
Economic Opportunity	No	Based on surveys and public opinion
Net public finance	No	Out of the scope
Mobility space usage	Yes	Relevant taking into account the focus on infrastructure
Emissions of greenhouse gases (GHG)	Yes	It has been identified as a crucial indicator
Congestion and delays	No	There is no representation of roads or corridors
Energy efficiency	Yes	Relevant taking into account the context
Opportunity for active mobility	Yes	Relevant taking into account the focus on infrastructure
Intermodal integration	No	Not represented due to the assumption that a trip consists of one transportation mode

Table 3.2: Overview of Sustainable Urban Mobility Indicators (continued)

Indicator	Possible representation	Reason for Decision
Comfort and pleasure	No	Based on surveys
Security	No	Based on surveys and out of the scope
Occupancy rate	Yes	Relevant taking into account the focus on infrastructure
Motorization rate	Yes	Relevant taking into account the focus on infrastructure
Modal split	Yes	Relevant as previously explained
Smartphone penetration	No	Outside the current study's focus
Vehicle miles travelled per capita	Yes	Relevant given the focus on origin destination matrices and infrastructure available
Speed in the transport network	No	Not a priority for current study
Car friendliness of the city center	No	Not a priority for current study
Availability of public transport cards	No	Not critical for analysis

The next step included assigning priorities of representation to the indicators, taking into account the effort needed to allocate to create the subsystems that represent the dimensions necessary. All of these indicators could be eventually represented, expanding on the existing model. The priority is set as 1 to 5, 5 meaning high priority. Some were assigned lower priorities because there was insufficient data to calculate them, or their implementation would be an extreme simplification of reality. Fatalities are a good example; even though it is a relevant measure, the representation would have to be a connection with vehicles on the road, simplifying reality, this indicator would be better represented with more detailed approaches to traffic and pedestrian behavior; other indicators fit in more naturally to the model being represented, so they were assigned a higher priority. The results are available in Table 3.3.

Table 3.3: Priority assigned to target Indicators.

Indicator	Priority (1-5)
Affordability of public transport for the poorest group	5
Air polluting emissions	3
Fatalities	3
Access to mobility services	4
Commuting travel time	4
Mobility space usage	4
Emissions of greenhouse gases (GHG)	5
Energy efficiency	3
Opportunity for active mobility	3
Occupancy rate	4
Motorization rate	4
Modal split	5
Vehicle miles travelled per capita	3

Taking into account Table 3.3, the final indicators selected were:

Affordability of public transport for the poorest group, given by:

$$AI = \frac{\sum_i TPT_i \cdot F10km_i}{Minc_{25\%}} \times 60 \quad (3.1)$$

Where:

AI = Affordability Index of public transport for the poorest population quartile

TPT_i = Monthly percentage of PT trips with PT mode i [%]

$F10km_i$ = Fare 10km PT trip with PT mode i [monetary unit]

$Minc_{25\%}$ = Average monthly income of poorest population quartile [monetary unit]

i = Available public transport mode [type]

60 = Sixty trips per month

Mobility space usage, given by:

$$LUM = \frac{\sum_i (LD_i + LI_i)}{Cap} \quad (3.2)$$

Where:

LUM = Land use for mobility applications [m^2]

LD_i = Direct Land use for mobility mode i [m^2]

LI_i = Indirect Land use for mobility mode i [m^2]

i = Mobility mode [#]

Cap = Capita or number of inhabitants in the city [#]

Emissions of greenhouse gases (GHG), given by:

$$G = \frac{\sum_{ij} A_{ij} (\sum_k S_{jk} I_{jk} (C_k (1 + F_{ijk}) + W_k))}{Cap} \quad (3.3)$$

Where:

G = Greenhouse gas emission [tons CO_2 eq./cap. per year]

Ck = Tank to wheel CO_2 emission per energy type unit considered [kg/l or kg/kWh]

Wk = Well to tank CO_2 equivalent emission per energy type unit considered [factor]

A_{ij} = Activity volume (distance driven by transport mode i and vehicle type j) [million km per year]

S_{jk} = Share of fuel type k per vehicle type j [fraction]

I_{jk} = Energy intensity per distance driven for vehicle type j and fuel type k [l/km or MJ/km or kWh/km]

Cap = Capita or number of inhabitants in the city [#]

F_{ijk} = Non- CO_2 GHG correction (CO_2 equivalent) [factor]

k = Energy type (petrol, diesel, bio-fuel, electricity, hydrogen etc.) [type]

i = Transport mode [type]

Occupancy rates, given by:

$$OR_i = \frac{DT_i}{MC_i} \quad (3.4)$$

Where:

OR_i = Occupancy Rate for public transport mode i [%]

DT_i = Daily trips using public transport mode i [#]

MC_i = Maximum capacity available for public transport mode i [#]

i = Available public transport mode [type]

Motorization rate, given by:

$$MR = \frac{MV}{Cap} \times 1000 \quad (3.5)$$

Where:

MR = Motorization Rate [vehicles per 1,000 inhabitants]

MV = Number of motorized vehicles [#]

Cap = Capita or number of inhabitants in the area [#]

Modal split, given by:

$$MS_i = \frac{T_i}{T_t} \times 100 \quad (3.6)$$

Where:

MS_i = Modal Split for transport mode i [%]

T_i = Number of trips with transport mode i [#]

T_t = Total number of trips with all transport modes [#]

i = Transport mode [type]

The selection of indicators then influences which variables are represented in the system and the subsystem's design evolves from these. There was a focus on implementing clear different subsystems with interactions between them, forming feedback loops and respecting the principles of the System Dynamics approach.

3.4 Implementation Pipeline

After defining the main modules of the model and what variables are necessary to represent, in phase 1, the Conceptual model is presented. For phases 2 and 3 of the MPMF modeling framework, the implementation pipeline showcased in Figure 3.4 will be employed.

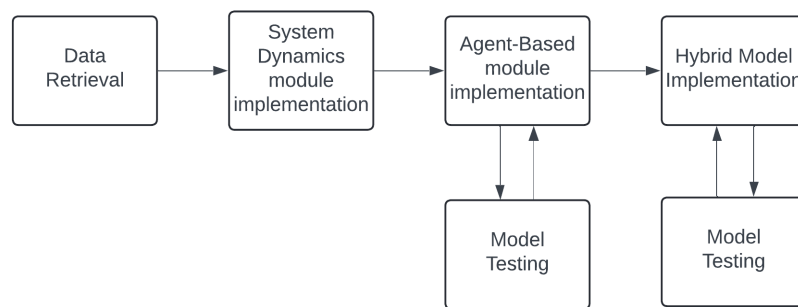


Figure 3.4: Diagram representing the proposed Implementation Pipeline.

This pipeline approach ensures a structured development process. Each module will be developed in isolation, allowing for focused and specialized progress. Subsequently, these modules will be fully integrated, ensuring that they interact seamlessly at every step. This modular development strategy not only facilitates easier debugging and refinement but also promotes a more robust final model.

By adopting this method, we aim to enhance the reliability and accuracy of the overall model. The final integrated model will undergo testing against real-world data, ensuring that it performs reliably and meets the intended specifications.

Chapter 4

Implementation

Following the implementation pipeline presented, this chapter aims to explain the implementation of each module and how they interact. Both the System Dynamics and Agent-Based modules will be presented as stand-alone models, with the knowledge that they were designed to be integrated into a Hybrid Model.

4.1 System Dynamics Module

This section aims to present the System Dynamics part of the model. The goal is to explain the subsystems represented, the main feedback loops, and all the assumptions made during the development of the model.

4.1.1 Main System

This subsection aims to provide a clear view of the system through the main feedback loops that support it. In Figure 4.1, it is possible to observe the main subsystems of the System Dynamics model created. The focus was to expand the Urban Model to represent the mobility systems through infrastructure and present the target indicators. So the main subsystems include the Urban subsystem, Socioeconomic subsystem, Infrastructure subsystem, Greenhouse Gases Emissions subsystem, and finally, the resulting indicators. The next subsections will explore each of them and enumerate the variables that define them.

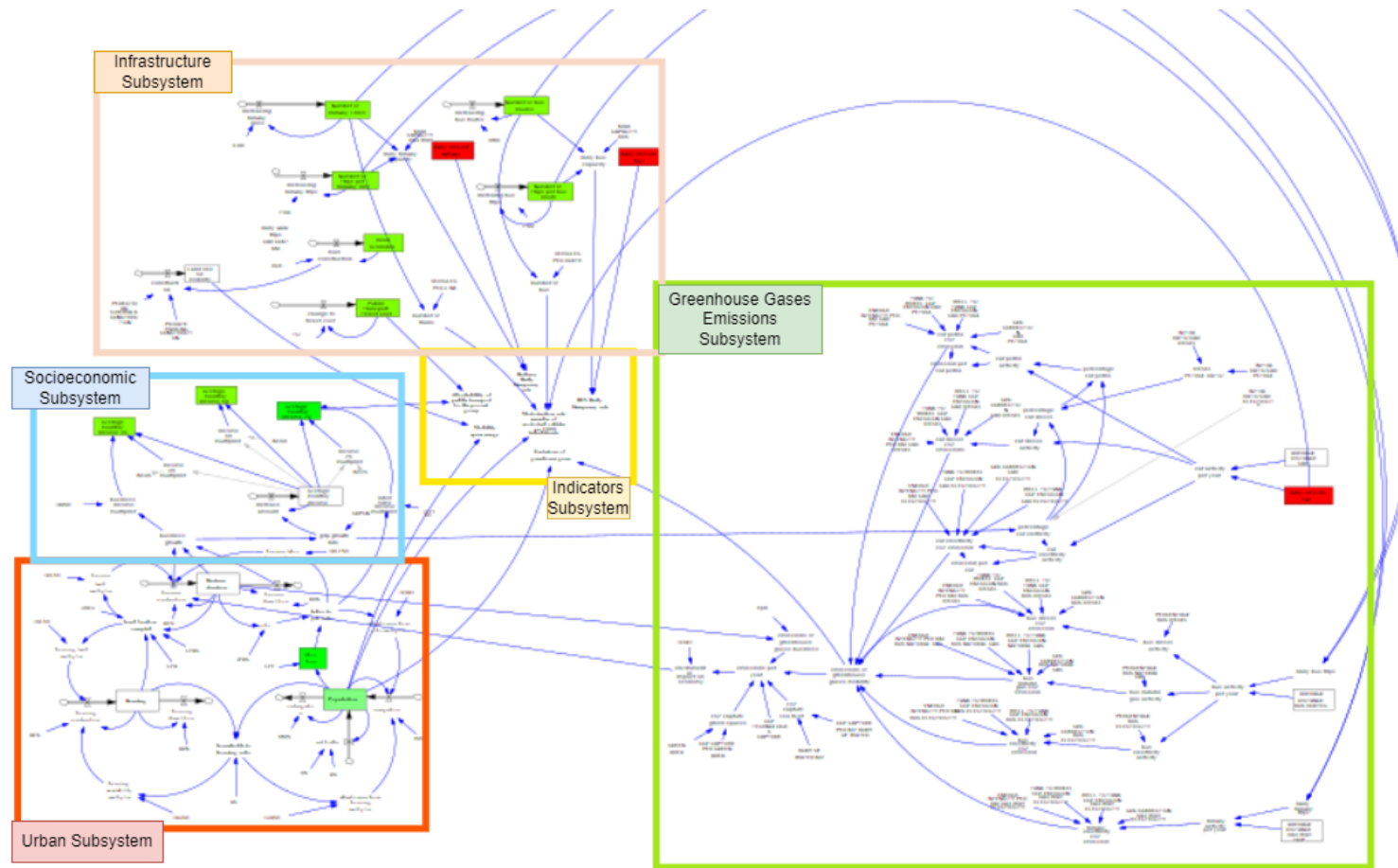


Figure 4.1: Main SD model structure.

In Figure 4.2, the main components of the module are presented. The diagram only presents some of the relevant variables to present the inner workings of the system at a higher level than the previous diagram. Given that the dynamics of a system are majorly determined by defining feedback loops (Sterman, 2000), explaining and justifying the present main synergies that dictate the workings of the model will be the starting point of this analysis. In this subsection, only the loops represented through just System Dynamics are presented; the complete final model is available in Section 4.3.2. The feedback loops and relationship between variables are currently made through assumptions inspired by connections seen in the literature. Given more readily available data, it would be relevant to perform a correlation analysis to achieve trustworthy connections. In the next subsections, each subsystem and all the variables defining it will be described in greater detail.

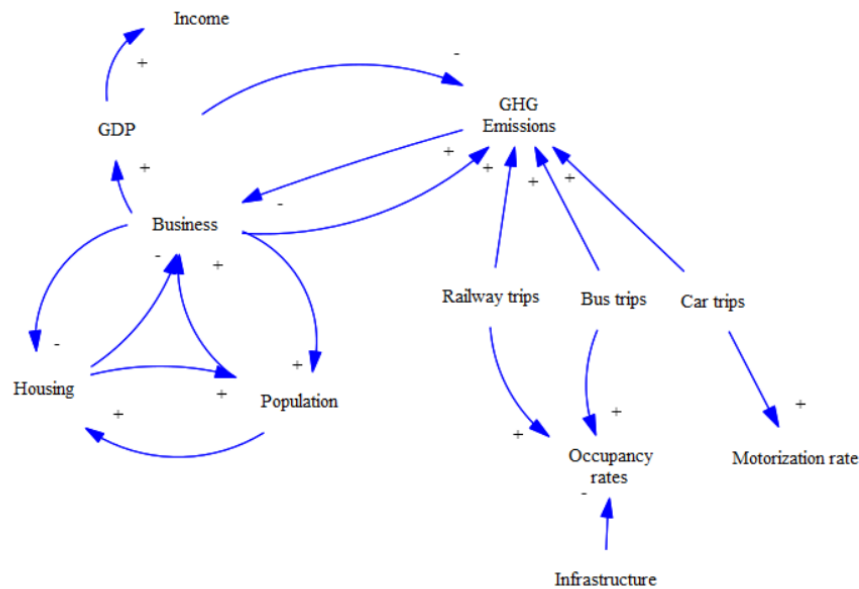


Figure 4.2: SD model Main Causal Loop Diagram.

In Figure 4.3, a reinforcing loop is showcased. The higher the number of people, the higher the demand for housing. In turn, high house availability, in theory, means lower prices and better conditions for people to stay and move to the city. It is a self-reinforcing loop.



Figure 4.3: Feedback loop regarding population and housing.

In Figure 4.4, the increase in population means a higher labor force available, which stimulates business, which in turn stimulates the city's attractiveness for new citizens. It is a self-reinforcing loop.



Figure 4.4: Feedback loop regarding population and business.

In Figure 4.5, the number of houses is connected to the land available. If there is new construction, the land available decreases and prices may increase; therefore, the incentive for more construction decreases. It is a self-correcting loop because more housing construction can cause less housing construction.



Figure 4.5: Feedback loop regarding housing

In Figure 4.6, the number of businesses is also connected to the land available. The logic is exactly the same as the previous; it is controlled by the land available, which predicts the facility of construction, given that less space can mean higher costs. It is a self-correcting loop because more business construction causes less business construction.



Figure 4.6: Feedback loop regarding business

The self-correcting feedback loop represented in Figure 4.7 aims to represent the business's emission of Greenhouse gases while also showcasing pollution's negative effects on the economy and business construction.



Figure 4.7: Feedback loop regarding business and GHG Emissions.

Finally, the impact of the fleet's fuel share on the resulting GHG emissions. In the model, the increased investment in electric vehicles is associated with GDP growth. As presented in Figure 4.8, GDP growth leads to higher electricity-fueled vehicles in the fleet. These vehicles will emit less greenhouse gasses, meaning less harm to the businesses in the city and, as a result, GDP growth. It is a self-reinforcing feedback loop.



Figure 4.8: Feedback loop regarding GDP and GHG Emissions.

It was relevant to structure the system into clear feedback loops to follow the principles of the System Dynamics modeling approach. However, a lot is represented as outputs of the model, such as Occupation rates, Motorization Rates, Affordability of Public Transport to the poorest group, Land Usage for mobility, etc. These are relevant metrics of urban sustainable plans that need representation in the model but do not necessarily incorporate a feedback loop. As previously stated, some components only form a loop when integrated with the Agent-Based module of the model.

In the following subsections, each subsystem will be explored in detail. For each, there will be tables representing all variables impacting the system so the model is clear.

4.1.2 Urban Subsystem

To tackle the lack of knowledge regarding economics and urban development necessary to comprehensively represent the urban environment, a preexisting model was chosen to start from. At the base of the model developed is the "Urban Model" already mentioned in Subsection 2.1.1. It is used to represent the city being studied clearly and then expanded to represent the necessary elements to test mobility policies.

As previously mentioned, the Urban Model comprises three main sectors: Population, Business, and Housing. The projections of the city's future are made up of equilibrium among these. The model started with the data for the city of Gondomar in 2021, and it predicted the next 50 years. In Figure 4.10 are represented the main variables of the model, showing the predicted growth for the city. The number of people living in the city is expected to decrease in the next few years but increase in the long run after 2035, arriving at 318167 people in 2071. The model also projects high economic growth with the constant creation of new Businesses that attract immigration to the city. In terms of housing, the estimates are that it merely slowly increases given that there is a high number of houses compared to the number of people currently living in Gondomar.

In the modeling process, several simplifications and assumptions are made to streamline the analysis and ensure manageability. For example, the model assumes the city is a closed environment, but in reality, a lot of the people in Gondomar end up working in municipalities close by, such as Porto. This explains the high initial Labor to job ratio present in Figure 4.10. The active population is bigger than the jobs available because of the number of workers that commute to other cities nearby. It is also assumed that all houses are or will be fully occupied. This assumption may not always hold true in real-world scenarios, where factors such as varying occupancy rates, housing market dynamics, and demographic shifts can affect the actual utilization of housing stock. Beyond this assumption, other key simplifications include the constant creation of new businesses and the assumption that these businesses will continuously attract immigration to the city. This overlooks potential economic downturns, changes in business trends, and external economic influences that might affect business growth and immigration patterns. Additionally, the model presumes a high economic growth rate without accounting for potential economic fluctuations or unforeseen events that could impact economic stability. It also simplifies demographic changes by not fully considering factors such as changes in birth and death rates, policy changes,

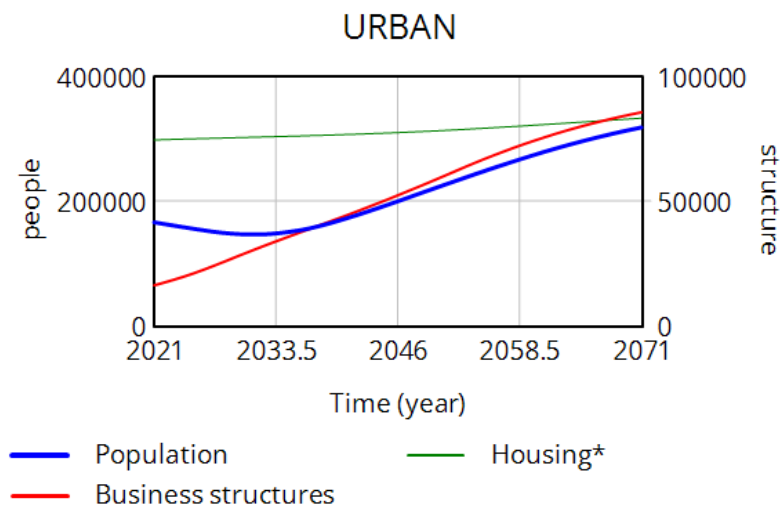


Figure 4.9: Represents the projection of the three main components of the model for the city Gondomar.

and broader social trends that could influence population dynamics. These assumptions, while necessary for constructing a coherent and functional model, highlight the need for caution when applying these projections to real-world scenarios, as they may not fully capture the complexity and variability of real-life conditions. Nonetheless, the main goal of this dissertation is to explore the synergy between the two modeling approaches. The focus is on capturing the main relevant components to represent the evolution of the population and the changes in its behavior given different transportation policies.

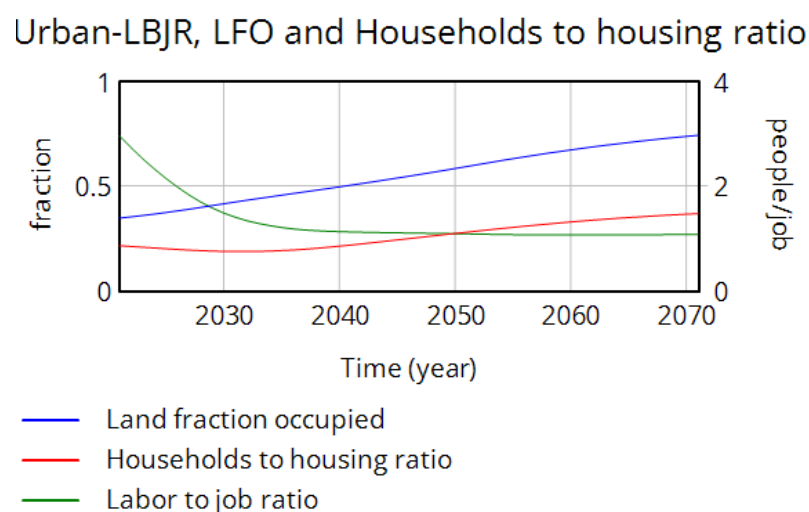


Figure 4.10: Ratios among the variables projected by the Urban Model for the city of Gondomar.

Further graphs showcasing the results of the Urban model for the city of Gondomar are available in the Appendix (Figures [A.1](#), [A.2](#), [A.3](#), [A.4](#)).

To provide full clarity to the model, in Table 4.1, the constants are clarified. In Table 4.2, the list of variables that are calculated in each iteration are presented. Finally, the stocks, as explained in Section 2.1.1, are listed in Table 4.3. The functions associated with this subsystem are available in the Appendix in Figures A.5, A.6, A.7, A.8, A.9, A.10.

Table 4.1: Constants in the Urban Model

Name	Units	Description
BCN	fraction/ year	Rate of new business constructions per year
BDN	fraction/ year	Rate of business demolitions per year
AREA	m ²	Total area available for new construction projects
LPBS	m ²	Average land area occupied per business structure
LPH	m ²	Average land area occupied per residential house
JPBS	jobs/ structure	Number of jobs generated per business structure
LPF	fraction	Fraction of the population that is part of the labor force
IMN	fraction/ year	Annual rate of immigration into the region
OMN	fraction/ year	Annual rate of outmigration from the region
BN	fraction/ year	Annual birth rate as a fraction of the population
DN	fraction/ year	Annual death rate as a fraction of the population
HS	people/ family	People per Household

Table 4.2: Variables in the Urban Model

Equation	Units
$\text{net births} = \text{Birth rate} \times (\text{BN} - \text{DN}) \times \text{Population}$	persons/year
$\text{outmigration} = \text{OMN} \times \text{Population}$	persons/year
$\text{immigration} = \text{IMR} \times \text{Population}$	persons/year
$\text{business demolition} = \text{BDN} \times \text{Population}$	structures/year

households to housing ratio = $\frac{\text{Population}}{\frac{\text{HS}}{\text{Housing}}}$	households/ housing unit
housing construction = $\text{HCN} \times \text{housing land multiplier} \times \text{housing availability multiplier} \times \text{Housing}$	structures/year
housing demolition = $\text{HDN} \times \text{Housing}$	units/year
labor force = $\text{LFPR} \times \text{Population}$	persons
labor to job ratio = $\frac{\text{Labor force}}{\text{Number of available jobs}}$	ratio
land fraction occupied = $\frac{(\text{Business structures} \times \text{LPBS} + \text{Housing} \times \text{LPH})}{\text{AREA}}$	fraction
business construction = $\text{BCN} \times \text{business land multiplier} \times \text{business labor force multiplier} \times$ $\text{Business structures} \times \text{environmental impact on economy}$	structures/year
attractiveness from housing multiplier = $\text{AHM}(\text{households to housing ratio})$	fraction
attractiveness from jobs multiplier = $\text{AJM}(\text{Labor to Job Ratio})$	fraction
business labor force multiplier = $\text{BLFM}(\text{labour to job ratio})$	fraction
business land multiplier = $\text{BLM}(\text{land fraction occupied})$	fraction
housing land multiplier = $\text{HLM}(\text{land fraction occupied})$	fraction
housing availability multiplier = $\text{HAM}(\text{households to housing ratio})$	fraction

Table 4.3: Stocks in the Urban Model

Equation	Units
Population = $\int (\text{net births} + \text{immigration} - \text{outmigration}) dt + \text{initial value}$	persons
Business structures = $\int (\text{business construction} - \text{business demolition}) dt + \text{initial value}$	structures
Housing = $\int (\text{housing construction} - \text{housing demolition}) dt + \text{initial value}$	units

4.1.3 Socioeconomic Subsystem

There is a special interest in describing the evolving characteristics of a population to see how their needs and priorities change through time. To achieve it, there was a focus on predicting the population's income and, therefore, purchasing power. The variables defining this subsystem are presented in Figure 4.11.

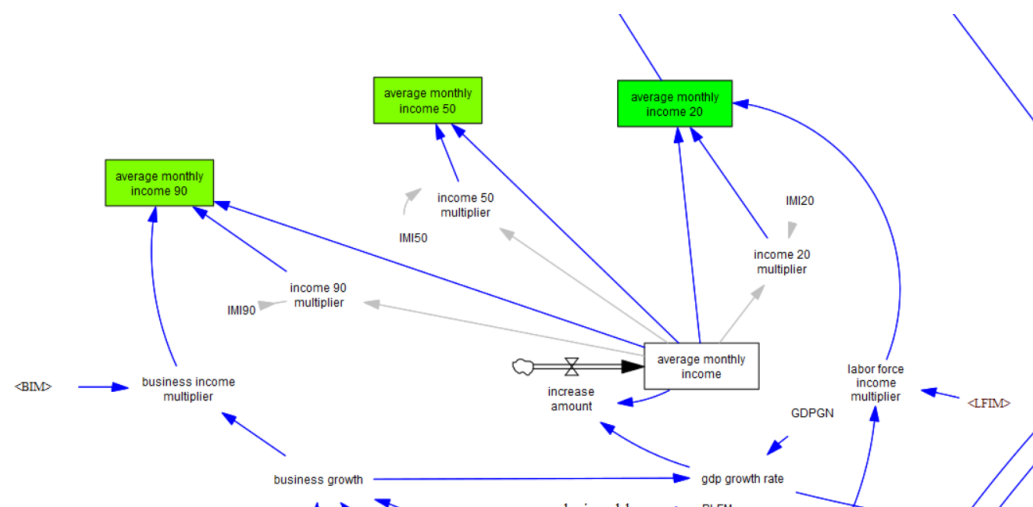


Figure 4.11: Vensim implementation of the socio-economic subsystem.

A projection of GDP was made through 'FORECAST.ETS' function in Excel. It was chosen because it accounts for seasonality, trends, and level changes in the data. This is an important aspect regarding a country's GDP since economic data often exhibits regular patterns and long-term trends influenced by factors such as economic cycles. It was calculated through data from 1990. Business growth also affects the projection of GDP. The calculation addresses the country and local conditions to attempt a reliable and trustworthy projection.

To project the future income of the population, the assumption was made that these would grow to the same proportion of the GDP. While understanding it is a simplification of reality, it was chosen to be able to predict endogenously the conditions of the population. The variables represented are the income rate through percentiles. The percentiles 20%, 50%, and 90% were chosen to represent the low, middle, and upper classes, respectively. These values were also chosen because of the data available. The goal is that they correspond to the average income of the bottom 20%, middle 70%, and top 10% of the population. To ensure variability, the income growth for the lower class was linked specifically to the 'labor-to-job ratio' variable. This linkage is based on the assumption that a lower labor-to-job ratio indicates more competitive job market conditions, disproportionately affecting the lowest percentile's income levels. The rationale for focusing on the lower class rather than other classes is that these individuals are more sensitive to changes in labor market conditions. A competitive job market tends to exert greater pressure on wages and employment opportunities for lower-income workers, making this variable a crucial determinant of their income growth. Figure 4.12 represents how labor availability affects income growth for the lower class, this relationship is represented under the function LFIM in the model. As explained, when the labor-to-job ratio is low, the income grows rapidly, while it decreases when there is more competition for positions. These values are an assumption and should be further calibrated to represent reality accurately.

Annual business growth is connected to the highest income percentile to capture the impact of broader economic trends on higher-income individuals. This linkage reflects the understanding

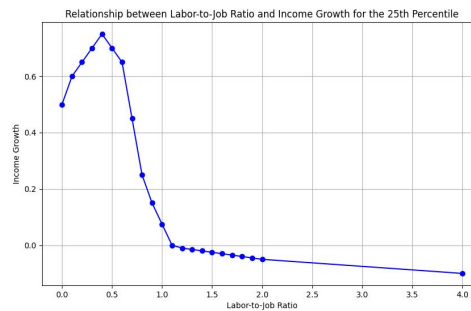


Figure 4.12: The effects of labor availability to growth of income for the 20% percentile.

that fluctuations more directly influence those in the upper-income bracket in business performance and economic expansion. As businesses grow and prosper, the wealthier segments of the population tend to experience significant income increases due to their investments, business ownership, and higher wages linked to corporate success. By associating annual business growth with the 90th percentile, the model accurately represents the income dynamics and economic conditions that predominantly affect the upper class. The relationship is represented in Figure 4.13; in the model, it is the BIM function. Similarly to the previous, it is an assumption, and it should be calibrated and validated further to represent reality accurately.

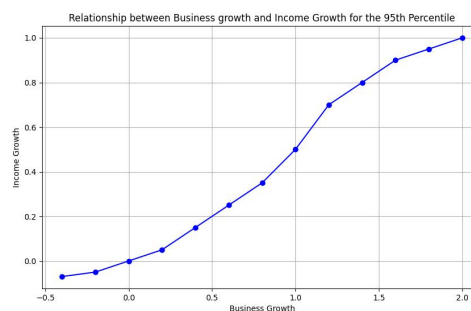


Figure 4.13: The effects of business growth to growth of income for the 90%-100% percentile.

The goal was to have a simple but effective projection of the population's economic conditions. While there are a lot of assumptions that hinder the predicting capabilities of the model, it captures how various factors represented in the system influence income distribution.

Similarly to the previous subsection, to provide full clarity to the model, in Table 4.4, the constants are clarified. In Table 4.5, a few variables that do not follow the typical structure are described, and in Table 4.6, the list of variables that are calculated in each iteration are presented. Finally, the stocks are listed in Table 4.7.

Table 4.4: Constants in the Socioeconomic subsystem

Name	Units	Description
IMI20	euro/month	Initial average income of 0%-20% of the population in order of income
IMI50	euro/month	Initial average income of 20%-90% of the population in order of income
IMI90	euro/month	Initial average income of 90%-100% of the population in order of income

Table 4.5: Misc. Variables in the Socioeconomic subsystem

Name	Units	Description
business growth	percentage/ year	Business Growth when compared to the previous year
gdpn	percentage/ year	Projection of GDP for each year based on previous data

Table 4.6: Variables in the Socioeconomic subsystem

Formula	Units
$\text{gdp growth rate} = \frac{\text{business growth} + \text{gdpn}}{2}$	fraction/year
$\text{income 20 multiplier} = \text{INITIAL} \left(\frac{\text{IMI20}}{\text{average monthly income}} \right)$	fraction/year
$\text{income 50 multiplier} = \text{INITIAL} \left(\frac{\text{IMI50}}{\text{average monthly income}} \right)$	fraction/year
$\text{income 90 multiplier} = \text{INITIAL} \left(\frac{\text{IMI90}}{\text{average monthly income}} \right)$	fraction/year
$\text{increase amount (average income)} = \text{GDP growth rate} \times \text{average monthly income}$	euro/month/year
$\text{average monthly income 20} = \text{average monthly income} \times (\text{income 20 multiplier} + \text{labor force income multiplier})$	euro/month
$\text{average monthly income 50} = \text{average monthly income} \times \text{income 50 multiplier}$	euro/month
$\text{average monthly income 90} = \text{average monthly income} \times (\text{business income multiplier} + \text{income 90 multiplier})$	euro/month

labor force income multiplier = LFIM(labor to job ratio)	factor
business income multiplier = BIM(business growth)	factor

Table 4.7: Stocks in the Socioeconomic subsystem

Formula	Units
Average monthly income = $\int$ increase amount $+ dt$ + initial value	euro

4.1.4 Infrastructure Subsystem

For simplification, it is described as infrastructure all the components that impact transport mode's accessibility, cost, and availability. It was a necessary implementation since the policies will be the changes made to the conditions available that may or may not impact modal choice decisions in the Agent-Based module.

The city of Gondomar was taken into account when designing the system. The transportation modes chosen are car/private vehicle, bus, railway, meaning both urban trains and metro, and walking. These choices were made by inspecting the data available ([Instituto Nacional de Estatística, I. P., 2018](#)) and checking the available modes in the city. By including both public and private transport options, the model can simulate a wider range of scenarios, from increased public transport usage due to lower fares to higher car usage due to improved road infrastructure. This versatility is essential for developing robust transportation policies that can adapt to changing conditions and user preferences.

For railways and buses, there are variables representing the number of routes, the number of trips on each route, and the ticket prices. To represent the conditions for private transport there are the area of roads available and the cost of riding cars per km. These were decided with the goal of being able to calculate some of the target indicators explained above. These variables do not have much impact on the System Dynamics module but will change the conditions described in the matrices that guide the agent's decisions. These connections will be explained in the next sections. These conditions are able to change at a rate of 5 to 5 years to account for the common transportation contract times in Portugal. Finding clear data for the target years was a major challenge since some of these, such as car cost per km, can be calculated in different ways, and the area dedicated to roads is not readily available. In Figure 4.11, there is the implementation of the subsystem.

The following Tables, namely Table 4.8, Table 4.9, and Table 4.10, present how this subsystem is structured.

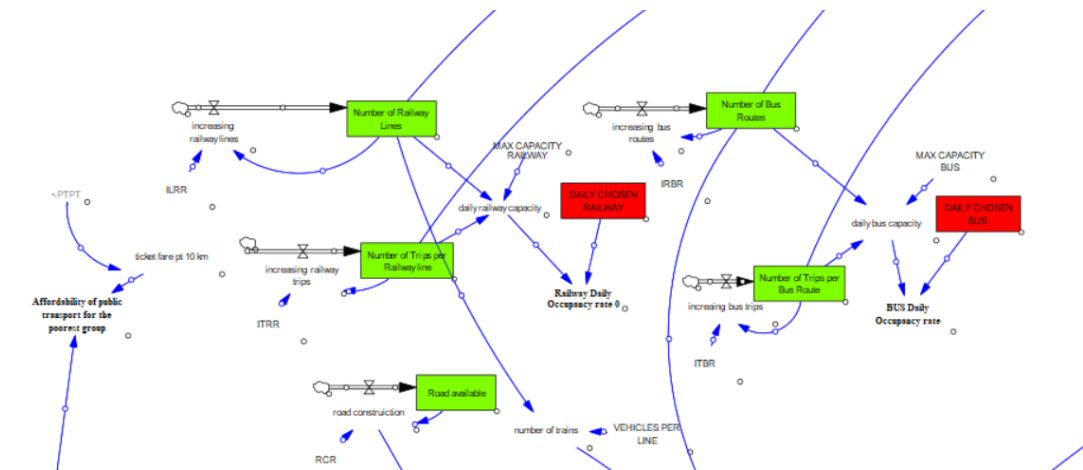


Figure 4.14: Vensim implementation of the infrastructure subsystem.

Table 4.8: Constants in the Infrastructure subsystem

Name	Units	Description
VEHICLES PER ROUTE	Vehicles	Number of vehicles assigned per bus route
MAX CAPACITY BUS	Passengers	Maximum number of passengers a bus can accommodate
MAX CAPACITY RAILWAY	Passengers	Maximum number of passengers a train can accommodate
VEHICLES PER LINE	Vehicles	Number of trains assigned per railway line
PEDESTRIAN SIDEWALK CONSTRUCTION	m ²	Sidewalk construction per year
PRIVATE PARKING CONSTRUCTION	m ²	Private Parking construction per year
ITBR	factor	Increase trips per bus rate
IRBR	factor	Increase routes by bus rate
ILRR	factor	Increase lines by railway rate
ITRR	factor	Increase trips per railway line rate

RCR	factor	Road Construction Rate
TCI	factor	Ticket Cost Increase
CCI	factor	Car Cost Increase

Table 4.9: Variables in the Infrastructure Subsystem

Formula	Units
increasing bus trips = Number of Trips per Bus Route $\times$ ITBR	trips per route
number of bus = VEHICLES PER ROUTE $\times$ Number of Bus Routes	buses
increasing bus routes = Number of Bus Routes $\times$ IRBR	routes
daily bus capacity = MAX CAPACITY BUS $\times$ Number of Trips per Bus Route $\times$ Number of Bus	passengers
increasing railway trips = ITRR $\times$ Number of Trips per Railway Line	trips per line
number of trains = VEHICLES PER LINE $\times$ Number of Railway Lines	trains
increasing railway lines = Number of Railway Lines $\times$ ILRR	lines
daily railway capacity = MAX CAPACITY RAILWAY $\times$ Number of Trips per Railway Line $\times$ Number of Trains	passengers
road construction = Road Available $\times$ RCR	m ²
change to car cost = Car Cost Km $\times$ CCI	euro/km
mobility infrastructure construction = road construction + PEDESTRIAN SIDEWALK CONSTRUCTION + PRIVATE PARKING CONSTRUCTION	m ² /year

Table 4.10: Stocks in the Infrastructure Subsystem

Formula	Units
Public Transport Ticket Cost = $\int$ change to ticket cost dt + initial value	euros
Number of Bus Routes = $\int$ increasing bus routes dt + initial value	routes
Number of Trips per Bus Route = $\int$ increasing bus trips dt + initial value	trips

Number of Bus = $\int$ increasing bus routes dt + initial value	buses
Number of Railway Lines = $\int$ increasing railway lines dt + initial value	lines
Number of Trips per Railway Line = $\int$ increasing railway trips dt + initial value	trips
Number of Trains = $\int$ increasing railway lines dt + initial value	trains
Road Available = $\int$ road construction dt + initial value	m ²
Land Use for Mobility = $\int$ mobility infrastructure construction dt + initial value	m ²

4.1.5 Greenhouse Gases Emissions Subsystem

As previously discussed, a worldwide effort exists to control greenhouse gas emissions. Therefore, the representation of the environmental consequences of policies regarding transportation is a must. When deciding which variables exactly to include, the indicator "Emissions of greenhouse gases (GHG)" (World Business Council for Sustainable Development, 2015) was used as a starting point. In Figure 4.15, Figure 4.16, Figure 4.17 and Figure 4.18 it is possible to view the implementation that will be described below.

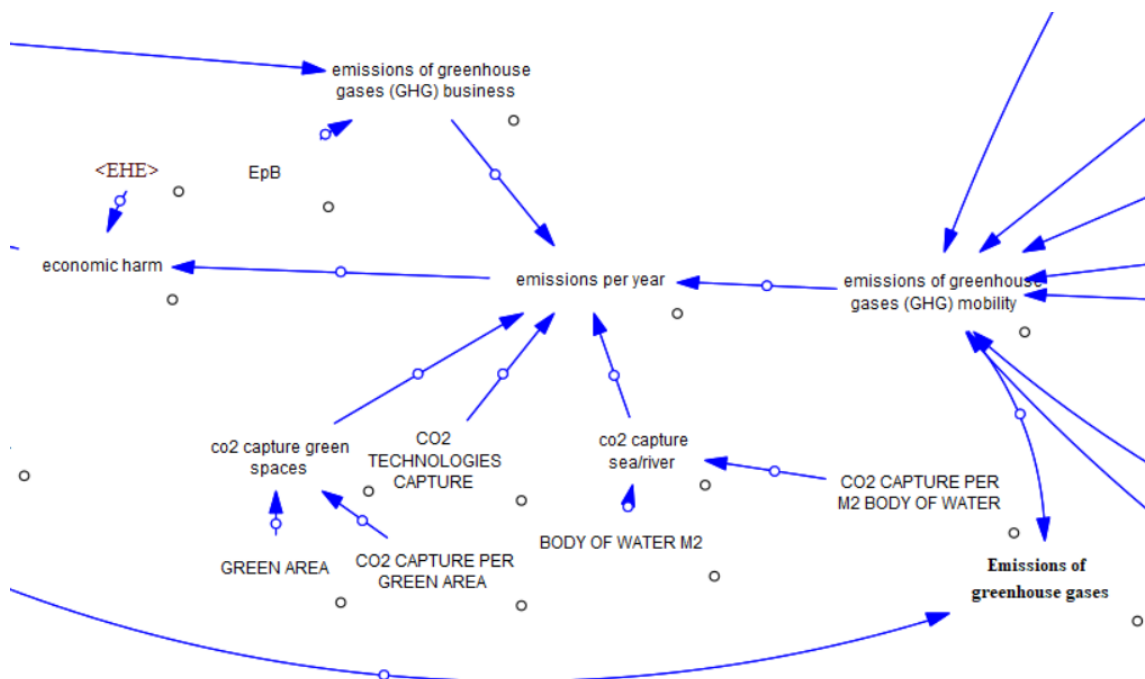


Figure 4.15: Vensim implementation of the emissions subsystem.

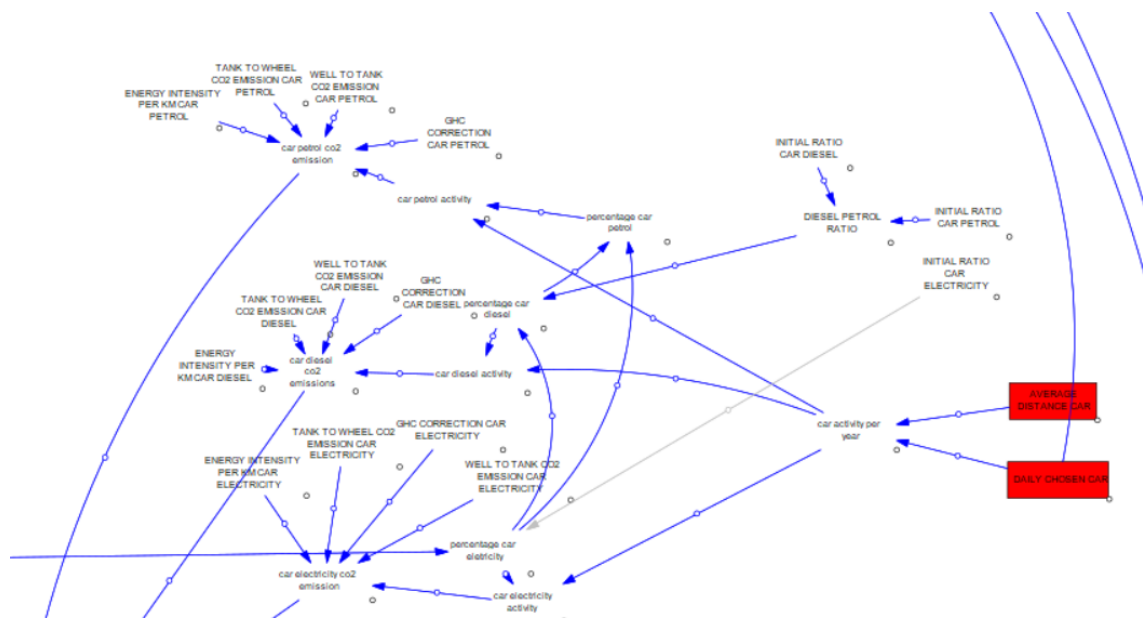


Figure 4.16: Vensim implementation of the car GHC emissions.

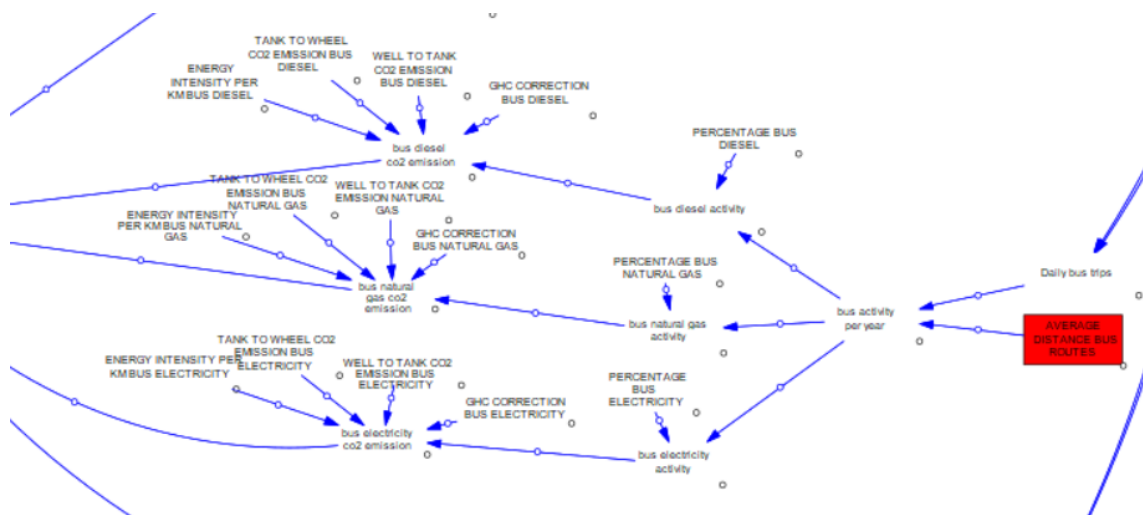


Figure 4.17: Vensim implementation of the bus emissions.

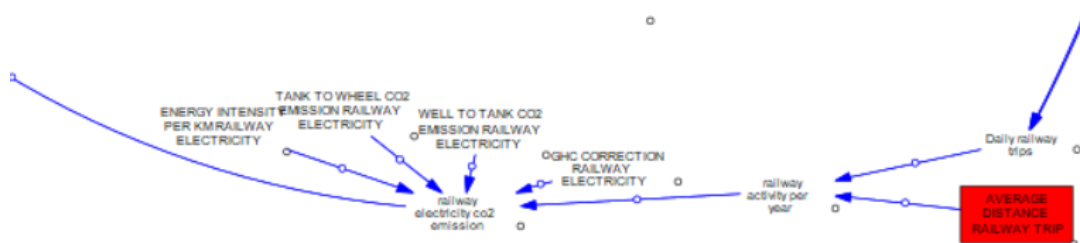


Figure 4.18: Vensim implementation of the railway emissions.

The impact of industry and transportation was considered to represent greenhouse gas emissions. Fuel share of public and private transportation vehicles is an important dimension of the transportation system. Different fuels have varying carbon intensities, so understanding the proportion of each fuel type used helps estimate overall emissions accurately. For instance, gasoline and diesel have higher carbon emissions than electricity when derived from renewable sources. Therefore, a detailed breakdown of fuel shares enables better tracking of emission sources and supports the development of targeted strategies to reduce GHG emissions in the transportation sector. It enables the implementation of policies regarding the incentive or disincentive of certain fuels.

To account for the trending growth in the share of electric vehicles in the fleet, it was assumed that the percentage of electric private vehicles on the road would grow with economic prosperity. This assumption was made considering the economic investment necessary to make the switch and the exponential growth expected to happen over time. The exact fuel types represented for each transport mode were defined considering Gondomar's reality. To represent the growth of the share of electric vehicles, the function represented in Figure 4.19 was used. That factor is then multiplied by the current share of electricity of the summed each year. The relationship is better explained in Table 4.13. The goal was to represent electrification as having a connection to economic prosperity, since there are necessary investments, but also represent how the growth is gradual at first but quickly speeds up as more and more population adhere to it. Here, a suggestion of a relationship is presented, but it should be validated with historical data. The goal was that the electric share began slowly rising, but the velocity increased with time to simulate expected behavior. The fuel share of public transport is currently constant.

Since economic growth in itself also leads to greenhouse gas emissions, there is a direct connection between the current number of businesses present in the city and the emissions.

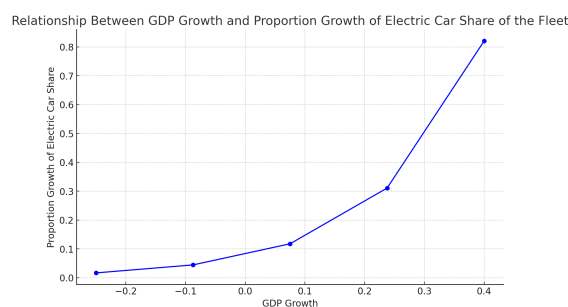


Figure 4.19: The effects of GDP growth on the percentual growth of electric share of the private car fleet.

To be able to have full feedback loops, respecting the principles of System Dynamics, there is a connection between GHG emitted and Business Construction. It is made under the assumption that high GHG emissions can disrupt business operations, supply chains, and overall economic stability. The emissions are normalized and contribute to the prospect GDP growth. The relationship is represented in Figure A.11. There was not enough data to create a validated relationship. The

solution was to assume some but minimal impact. This should be replaced by a proper study of the consequences of Greenhouse gases, which was not possible to perform during this dissertation.

Mitigation measures can also be employed. In the model presented, the ones chosen were the presence of bodies of water, green areas, and capturing technologies. They are not exactly part of mobility policies, but it was considered important to represent more accurately emissions as a subsystem and how it can impact other subsystems.

It is possible to observe that an extensive list of variables is included in this subsystem. This was due to the desire to fully represent this subsystem in Vensim. It could be desirable in the future to use a different approach to simplify the process while still including the results in the main feedback loops. This subsystem was created to represent the "Emissions of greenhouse gases" indicator from [World Business Council for Sustainable Development \(2015\)](#). Most of the variables and units are defined from the formula from this indicator. Similarly to the previous subsection, Table 4.11, Table 4.12, and Table 4.13 enumerate each variable and how they are calculated.

Table 4.11: Constants in the Mobility subsystem

Name	Units	Description
DIESEL PETROL RATIO	ratio	Ratio of diesel to petrol cars
INITIAL RATIO CAR PETROL	fraction	Initial share of petrol cars
INITIAL RATIO CAR DIESEL	fraction	Initial share of diesel cars
INITIAL RATIO CAR ELECTRICITY	fraction	Initial share of electric cars
PERCENTAGE BUS NATURAL GAS	fraction	Percentage of natural gas buses in the bus fleet
PERCENTAGE BUS DIESEL	fraction	Percentage of diesel buses in the bus fleet
PERCENTAGE BUS ELECTRICITY	fraction	Percentage of electric buses in the bus fleet
AVERAGE DISTANCE CAR	km/trip	Average distance driven by cars per trip

AVERAGE DISTANCE RAILWAY TRIP	km/trip	Average distance of railway per trip
AVERAGE DISTANCE BUS ROUTES	km/trip	Average distance of bus routes per trip
ENERGY INTENSITY PER KM CAR PETROL	l/km	Energy intensity per kilometer for petrol cars
ENERGY INTENSITY PER KM CAR DIESEL	l/km	Energy intensity per kilometer for diesel cars
ENERGY INTENSITY PER KM CAR ELECTRICITY	kWh/km	Energy intensity per kilometer for electric cars
ENERGY INTENSITY PER KM BUS NATURAL GAS	kg/km	Energy intensity per kilometer for natural gas buses
ENERGY INTENSITY PER KM BUS DIESEL	l/km	Energy intensity per kilometer for diesel buses
ENERGY INTENSITY PER KM BUS ELECTRICITY	MJ/km	Energy intensity per kilometer for electric buses
ENERGY INTENSITY PER KM RAILWAY ELECTRICITY	MJ/km	Energy intensity per kilometer for railway electricity
TANK TO WHEEL CO ₂ EMISSION CAR ELECTRICITY	Kg CO ₂ /l	CO ₂ emissions from tank to wheel for electric cars
TANK TO WHEEL CO ₂ EMISSION CAR DIESEL	Kg CO ₂ /l	CO ₂ emissions from tank to wheel for diesel cars
TANK TO WHEEL CO ₂ EMISSION CAR PETROL	Kg CO ₂ /l	CO ₂ emissions from tank to wheel for petrol cars

TANK TO WHEEL CO ₂ EMISSION BUS NATURAL GAS	Kg CO ₂ /kg	CO ₂ emissions from tank to wheel for natural gas buses
TANK TO WHEEL CO ₂ EMISSION BUS ELECTRICITY	Kg CO ₂ /MJ	CO ₂ emissions from tank to wheel for electric buses
TANK TO WHEEL CO ₂ EMISSION BUS DIESEL	Kg CO ₂ /l	CO ₂ emissions from tank to wheel for diesel buses
TANK TO WHEEL CO ₂ EMISSION RAILWAY ELECTRICITY	Kg CO ₂ /MJ	CO ₂ emissions from tank to wheel for railway electricity
WELL TO TANK CO ₂ EMISSION CAR DIESEL	Kg CO ₂ /l	CO ₂ emissions from well to tank for diesel cars
WELL TO TANK CO ₂ EMISSION CAR PETROL	Kg CO ₂ /l	CO ₂ emissions from well to tank for petrol cars
WELL TO TANK CO ₂ EMISSION CAR ELECTRICITY	Kg CO ₂ /MJ	CO ₂ emissions from well to tank for electric cars
WELL TO TANK CO ₂ EMISSION BUS DIESEL	Kg CO ₂ /l	CO ₂ emissions from well to tank for diesel buses
WELL TO TANK CO ₂ EMISSION BUS NATURAL GAS	Kg CO ₂ /kg	CO ₂ emissions from well to tank for natural gas buses
WELL TO TANK CO ₂ EMISSION BUS ELECTRICITY	Kg CO ₂ /MJ	CO ₂ emissions from well to tank for electric buses
WELL TO TANK CO ₂ EMISSION NATURAL GAS	Kg CO ₂ /kg	CO ₂ emissions from well to tank for natural gas

GHC CORRECTION CAR DIESEL	factor	Greenhouse gas correction factor for diesel cars
GHC CORRECTION CAR ELECTRICITY	factor	Greenhouse gas correction factor for electric cars
GHC CORRECTION CAR PETROL	factor	Greenhouse gas correction factor for petrol cars
GHC CORRECTION RAILWAY ELECTRICITY	factor	Greenhouse gas correction factor for railway electricity
GHC CORRECTION BUS ELECTRICITY	factor	Greenhouse gas correction factor for electric buses
GHC CORRECTION BUS NATURAL GAS	factor	Greenhouse gas correction factor for natural gas buses
GHC CORRECTION BUS DIESEL	factor	Greenhouse gas correction factor for diesel buses
GHC CORRECTION BUS DIESEL	factor	Greenhouse gas correction factor for diesel buses
CO ₂ CAPTURE PER M2 BODY OF WATER	tons CO ₂ /year	CO ₂ captured per square meter of body of water per year
BODY OF WATER M ²	m ²	Area of body of water in square meters
CO ₂ CAPTURE PER GREEN AREA	tons CO ₂ /year	CO ₂ captured per square meter of green area per year
GREEN AREA	m ²	Area of green space in square meters
EPB	tons CO ₂ /year	Emissions per business structure per year
CO ₂ TECHNOLOGIES CAPTURE	tons CO ₂ /year	CO ₂ captured by technologies per year

Table 4.12: Variables in the Emissions Subsystem

Formula	Units
$\text{percentage car diesel} = \frac{(1 - \text{percentage car electricity})}{1 + \text{DIESEL PETROL RATIO}}$	fraction
$\text{percentage car petrol} = 1 - \text{percentage car diesel} - \text{percentage car electricity}$	fraction
$\text{gdp electric cars multiplier} = \text{GDPEM}(\text{GDP growth rate})$	factor
$\text{electric share increase} = \text{gdp electric cars multiplier} \times \text{Percentage Car Electricity}$	fraction/year
$\text{car activity per year} = \text{AVERAGE DISTANCE CAR} \times \text{Daily chosen car} \times 365$	km/year
$\text{bus activity per year} = \text{AVERAGE DISTANCE BUS ROUTES} \times \text{Daily bus trips} \times 365$	km/year
$\text{railway activity per year} = \text{AVERAGE DISTANCE RAILWAY TRIP} \times \text{Daily railway trips} \times 365$	km/year
$\text{car diesel activity} = \text{car activity per year} \times \text{percentage car diesel}$	km/year
$\text{car electricity activity} = \text{car activity per year} \times \text{percentage car electricity}$	km/year
$\text{car petrol activity} = \text{car activity per year} \times \text{percentage car petrol}$	km/year
$\text{bus electricity activity} = \text{bus activity per year} \times \text{PERCENTAGE BUS ELECTRICITY}$	km/year
$\text{bus diesel activity} = \text{bus activity per year} \times \text{PERCENTAGE BUS DIESEL}$	km/year
$\text{bus natural gas activity} = \text{bus activity per year} \times \text{PERCENTAGE BUS NATURAL GAS}$	km/year
$\text{railway electricity activity per year} = \text{railway activity per year} \times \text{PERCENTAGE RAILWAY ELECTRICITY}$	km/year
$\text{car diesel CO}_2 \text{ emissions} = \text{car diesel activity} \times \text{ENERGY INTENSITY PER KM CAR DIESEL} \times (\text{TANK TO WHEEL CO}_2 \text{ EMISSION CAR DIESEL} \times (1 + \text{GHC CORRECTION CAR DIESEL}) + \text{WELL TO TANK CO}_2 \text{ EMISSION CAR DIESEL}) / 10^3$	tons CO ₂ /year
$\text{car electricity CO}_2 \text{ emissions} = \text{car electricity activity} \times \text{ENERGY INTENSITY PER KM CAR ELECTRICITY} \times (\text{TANK TO WHEEL CO}_2 \text{ EMISSION CAR ELECTRICITY} \times (1 + \text{GHC CORRECTION CAR ELECTRICITY}) + \text{WELL TO TANK CO}_2 \text{ EMISSION CAR ELECTRICITY}) / 10^3$	tons CO ₂ /year

Formula	Units
car petrol CO ₂ emissions = car petrol activity × ENERGY INTENSITY PER KM CAR PETROL × (TANK TO WHEEL CO ₂ EMISSION CAR PETROL × (1 + GHC CORRECTION CAR PETROL) + WELL TO TANK CO ₂ EMISSION CAR PETROL)/10 ³	tons CO ₂ /year
bus electricity CO ₂ emissions = bus electricity activity × ENERGY INTENSITY PER KM BUS ELECTRICITY × (TANK TO WHEEL CO ₂ EMISSION BUS ELECTRICITY × (1 + GHC CORRECTION BUS ELECTRICITY) + WELL TO TANK CO ₂ EMISSION BUS ELECTRICITY)/10 ³	tons CO ₂ /year
bus diesel CO ₂ emissions = bus diesel activity × ENERGY INTENSITY PER KM BUS DIESEL × (TANK TO WHEEL CO ₂ EMISSION BUS DIESEL × (1 + GHC CORRECTION BUS DIESEL) + WELL TO TANK CO ₂ EMISSION BUS DIESEL)/10 ³	tons CO ₂ /year
bus natural gas CO ₂ emissions = bus natural gas activity × ENERGY INTENSITY PER KM BUS NATURAL GAS × (TANK TO WHEEL CO ₂ EMISSION BUS NATURAL GAS × (1 + GHC CORRECTION BUS NATURAL GAS) + WELL TO TANK CO ₂ EMISSION NATURAL GAS)/10 ³	tons CO ₂ /year
railway electricity CO ₂ emissions = railway activity per year × ENERGY INTENSITY PER KM RAILWAY ELECTRICITY × (TANK TO WHEEL CO ₂ EMISSION RAILWAY ELECTRICITY × (1 + GHC CORRECTION RAILWAY ELECTRICITY) + WELL TO TANK CO ₂ EMISSION RAILWAY ELECTRICITY)/10 ³	tons CO ₂ /year
emissions of greenhouse gases mobility = car diesel CO ₂ emissions + car electricity CO ₂ emissions + car petrol CO ₂ emissions + bus diesel CO ₂ emissions + bus electricity CO ₂ emissions + bus natural gas CO ₂ emissions + railway electricity CO ₂ emissions	tons CO ₂ /year
CO ₂ capture green spaces = CO ₂ CAPTURE PER GREEN AREA × GREEN AREA	tons CO ₂ /year
CO ₂ capture by sea/river = BODY OF WATER M ² × CO ₂ CAPTURE PER M ² BODY OF WATER	tons CO ₂ /year
emissions of greenhouse gases business = Business structure × EPB	tons CO ₂ /year
emissions per year = emissions of greenhouse gases business + emissions of greenhouse gases mobility – CO ₂ capture green spaces – CO ₂ capture by sea/river – CO ₂ TECHNOLOGIES CAPTURE	tons CO ₂ /year

Formula	Units
environmental impact on economy = EHE(emissions per year)	factor

Table 4.13: Stocks in the Emissions Subsystem

Formula	Units
Electric car percentage = $\int \text{electric share increase } dt + \text{initial value}$	fraction

4.1.6 Indicators

Finally, the variables left correspond to the target indicators and extra variables to get them. These are calculated through the values presented in the subsystems and Agent-Based module. Modal split is a result of the Agent-Based module, therefore it is not presented here. Similarly to before, the variables are described in Table 4.14, and Table 4.15.

Table 4.14: Misc variables in the Indicators subsystem

Name	Units	Description
daily chosen car	trips/day	It consists of the number of trips by car in a typical day. It is the output of the Agent-Based module
daily chosen bus	trips/day	It consists of the number of citizens that chose to ride the bus in a typical day. It is the output of the Agent-Based module
daily chosen railway	trips/day	It consists of the number of citizens that chose to take the metro/urban train in a typical day. It is the output of the Agent-Based module

Table 4.15: Variables in the Indicators Subsystem

Formula	Units
Emissions of greenhouse gases = $\frac{\text{emissions of greenhouse gases mobility}}{\text{Population}}$	tons CO ₂ /capita
Mobility space usage = $\frac{\text{Land Use for mobility}}{\text{Population}}$	m ² /capita
BUS Daily Occupancy rate = $\frac{\text{daily chosen bus}}{\text{daily bus capacity}}$	fraction

Formula	Units
Railway Daily Occupancy rate = $\frac{\text{daily chosen railway}}{\text{daily railway capacity}}$	fraction
Motorization rate = $\left(\frac{\text{daily chosen car}}{2} + \text{number of bus} + \text{number of trains} \right) \div \text{Population} \times 1000$	vehicles/1000 people
Affordability of public transport for the poorest group = $\frac{\text{Public Transport Ticket Cost}}{\text{average monthly income } 20} \times 60$	vehicles/1000 people

4.2 Agent Based Module

This section explores the implementation and results of the system's Agent-Based module. Similarly to the previous section, it will be explored as a stand-alone model, even though it was designed to be integrated with the System Dynamics module. As mentioned, the approach is based on matrices describing infrastructure conditions and travel demand. There is no representation of roads but of transportation costs between each Origin-Destination pair. It was designed to have low computational complexity but still capture traveler's behaviors. In all modal choice approaches the following assumptions are made:

- Each agent chooses only one transportation mode for a trip.
- Value of travel time is defined as the agent's income divided by 170, the number of hours per month considered; it encapsulates the value of an hour for each agent, which impacts their choices.
- Car speed is 80 km/h.
- Bus speed is 30 km/h.
- Walking speed is 4.54 km/h.

4.2.1 Agents

The simulation corresponds to one single typical day. Each agent has an origin, a destination, and the hour at which they wish to travel. The origin-destination matrix and travel times were created from the study in the area. This data was obtained from the [Instituto Nacional de Estadística](#). Where data was not available, it was estimated based on the number of people living in each location. Each agent is attributed an origin and a destination based on the distribution of trips through the matrix.

It was relevant to assign income levels. There are four kinds of income levels based on activity and/or class: not active, meaning students and people over 65, lower class, medium class, and higher class. There is a 67% chance each agent is of working age, and because the classes correspond to income level percentiles, for working age, the distribution is 20% lower class, 70%

medium, and 10% high. These were decided based on correspondence with the System Dynamics module.

In the model, agents who are not of working age do not have access to cars. The access to buses and railways is estimated based on the percentage of citizens living within a station's kilometer range. These are estimated to be the same across agent's start points. The availability of a mode is determined through the matrices, which will be explained in the next section. Each agent is assigned the distance to a station for the origin and the destination, meaning the first and last mile, being up to 1 km for each. Each agent can also have a preference regarding transportation mode, which will be explored in further sections.

The distribution of income, active population, and preferences are the same across agents with different origin points.

4.2.2 Environment

The environment is defined with matrices. To obtain data to study mobility in the city of Gondomar, matrices were developed to characterize each transportation mode's conditions. Information from Google Maps, UNIR, the bus service that has activity in Gondomar, and Metro do Porto was used to describe the conditions of each Origin-Destination pair for each transportation mode. These define all the necessary conditions for agents to make choices. The matrices developed include:

- Road distances - Distance in km between key points in the origin-destination pair.
- Road capacity - Defines the capacity per hour of the path between the origin-destination pair.
- Railway trip time - Defines railway trip's time length in minutes, being infinite if there is no connection.
- Railway wait time - Defines the average wait time for railway trips for each origin-destination pair.
- Bus wait time - Defines the average wait time for bus trips for each origin-destination pair.

These define the characteristics of the environment and can be changed to demonstrate changing infrastructure.

4.2.3 Congestion

To include agents learning from the environment and being affected by other agent's behavior there is a notion of congestion. This was implemented using the Bureau of Public Roads, given by:

$$T = T_0 \times \left(1 + a \times \left(\frac{D}{C} \right)^b \right) \quad (4.1)$$

Where:

- T is the travel time on the link.
- T_0 is the free-flow travel time.
- a and b are empirically determined parameters.
- D is the demand or traffic volume.
- C is the capacity of the link.

The values used for the vehicle per hour capacity of the roads are in the annex, but they are estimations due to the lack of data available. It was observed that in five iterations the model's predictions stabilized. These results are displayed in Figure 4.20. Given the simplicity of the environment, it stabilizes quickly. This is beneficial, as the goal is to maintain the model at a relatively low computational cost. In this implementation, the agents only have access to the state from the last iteration. In future work, Reinforcement Learning could be employed to create more sophisticated agents.

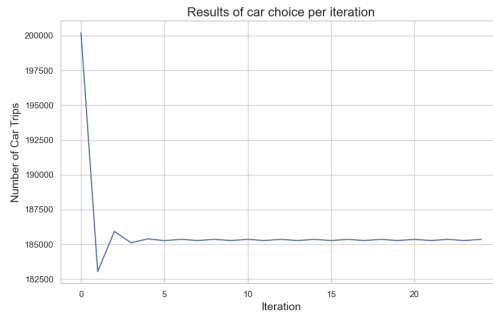


Figure 4.20: Analysis of results in each iteration

4.2.4 Cost-based modal choice

The first modal choice implementation consists of a greedy algorithm where each agent calculates the cost of each available mode for their trip and selects the one with the lowest cost.

This section outlines the cost functions for four primary modes of transportation: car, bus, railway, and walking. Each mode's cost function incorporates different factors, such as travel time, distance, and monetary expenses, to represent the overall utility from the agent's perspective. Below are the detailed formulations of these cost functions.

The car cost function is defined as:

$$C_C = T \cdot VoT + C \cdot D \quad (4.2)$$

Where:

C_C = Car Cost

T = Travel Time

V = Value of Travel Time

C = Car Cost per Kilometer

D = Distance

Travel time is defined using the BPR function explained above.

The Bus cost function is defined as:

$$C_B = \left(W + \frac{FM}{WS} + \frac{LM}{WS} + \frac{D}{BS} \right) \cdot VoT + TC \quad (4.3)$$

Where:

C_B = Bus cost

W = Wait Time

FM = First Mile

LM = Last Mile

WS = Walking Speed

D = Distance

BS = Bus Speed

VoT = Value of Travel Time

TC = Ticket Cost

For railway, the utility function is given by:

$$C_R = \left(T + W + \frac{FM}{WS} + \frac{LM}{WS} \right) \cdot VoT + TC \quad (4.4)$$

Where:

C_R = Railway Cost

T = Time Trip

W = Wait Time

FM = First Mile

LM = Last Mile

WS = Walking Speed

VoT = Value of Travel Time

TC = Ticket Cost

Finally, the walking cost is defined as:

$$C_W = \frac{D}{WS} \cdot VoT \quad (4.5)$$

Where:

C_W = Walk Cost

D = Distance

WS = Walking Speed

VoT = Value of Travel Time

4.2.5 Attractiveness Random Factor

Citizens often behave according to preconceived notions or preferences. Capturing real-world variability is essential in modeling because numerous, often unpredictable factors influence individuals' transport mode choices. The model attempts to replicate the inherent variability in human preferences and perceptions by introducing a random attractiveness factor. This approach acknowledges that the same transport mode may be perceived differently by different individuals or even by the same individual under different circumstances.

Purely deterministic models can oversimplify complex behaviors, leading to less realistic outcomes. Introducing a stochastic element via the random attractiveness factor adds to the complexity and unpredictability of real-world decision-making.

In this approach, each agent has preferences that impact the perceived costs when making the choices. The sum of the preferences for the transport modes is 1. This factor will then multiply the cost described previously and ultimately affect the agent's decision.

The modified cost C_i for each transportation mode is given by:

$$C_i = \alpha_i \cdot C_{W_i} \quad (4.6)$$

Where:

C_i = Perceived cost for mode i

α_i = Random attractiveness factor for mode i

C_{W_i} = Baseline cost for mode i

i = Transportation mode

In this equation, C_i adjusts the baseline cost C_W according to how much the individual values or prefers the transport mode.

4.2.6 The Logit Model

There was an interest in exploring different modal choice approaches and comparing them. Logit offers the possibility to discover the population's priorities and, with that, a better prediction of future outcomes. The Multinomial Logit (MNL) model determines the choice probabilities of each alternative as a function of the systematic portion of the utility of all alternatives. The general formula for the probability of choosing an alternative i (where $i = 1, 2, \dots, J$ from a set of J alternatives) is given by:

$$Pr(i) = \frac{\exp(V_{in})}{\sum_{t=1}^J \exp(V_{tn})} \quad (4.7)$$

where:

$Pr(i)$ = Probability of choosing alternative i

V_{in} = Systematic component of the utility for mode choice n by the traveler choosing alternative i

V_{tn} = Systematic component of the utility of the set of alternatives indexed by t

The variables that affect the utility for each transportation mode are the agent's Income, Trip cost, and Trip time. The general utility function is as follows:

$$V_i = \beta_{0i} + \beta_{1i}I + \beta_{2i}T + \beta_{3i}C \quad (4.8)$$

where:

V_i = Utility of transport mode i

β_{0i} = Intercept coefficient for transportation mode i

β_{1i} = Coefficient for income (I) for mode i

β_{2i} = Coefficient for time (T) for mode i

β_{3i} = Coefficient for cost (C) for mode i

I = Income

T = Time

C = Cost

i = Transportation mode

The values for each variable for each trip are calculated using methods similar to those described above for the cost-based method. It includes the cases where a transportation mode is unavailable because then time is the maximum possible.

All variables were normalized, and the model was calibrated using data from 2011 and 2017. A significant limitation is the lack of individual-level data; currently, only aggregate-level results are available. Access to individual-level data would enable further refinement and development of the model. Despite this limitation, data was artificially generated by creating a population that matched the described conditions for each year. The objective function was defined to compare the predicted distributions of different transport modes with the known distributions from historical data (2017 and 2011). The coefficients for the utility function were optimized by minimizing the mean squared error. The resulting coefficients are present in Tab.4.16.

Table 4.16: Coefficients for each transportation mode.

Mode	β_0	β_1	β_2	β_3
Car	0.13067237	0.60961852	-0.75787615	-0.51140001
Bus	-0.07634105	-0.41800807	-0.69477578	-0.56209977
Railway	-0.12861575	-0.67532208	-0.49421556	-0.31665572
Walking	0.18310248	-0.12728559	0.02689007	-1.32355362

4.2.7 Result Analysis

4.2.7.1 Validation

This section aims to validate and compare the modal choices explored. The Mean Absolute Percentage Error (MAPE) was selected as the error measure due to its intuitive interpretability and

suitability for the current context. It allows for straightforward comparisons between different modal choices by expressing errors as percentages of the actual values.

As it is possible to observe in Table 4.17, the Logit model performed much better than the other models, even with low-quality data to calibrate it. In the literature, less than 10% MAPE is considered Highly accurate forecasting (Montaño et al., 2013). While the greedy algorithm

Table 4.17: Comparison of Observed Data, Simulated Results, and Absolute Percentage Error (APE) for Different Approaches.

	Observed Data	Greedy		Random Factor		Logit	
		Simulated	APE (%)	Simulated	APE (%)	Simulated	APE (%)
Car split	0.652	0.5843	10.38%	0.3787	41.92%	0.6627	1.63%
PT split	0.227	0.2008	11.52%	0.1899	16.42%	0.1450	6.67%
Walking split	0.111	0.2148	93.54%	0.3715	234.71%	0.0952	14.23%
MAPE(%)			38.48%		95.56%		7.51%

based on cost matrices performs reasonably well for Public Transport (PT) split and Car with an Absolute Percentage Error (APE) of 11.52% and 10.38%, its predictions for Walking split are not accurate, with APEs of 93.54% respectively. The Mean Average Percentage Error is high mainly because of the walking percentage. This might be because the distance matrix indicates distances between closer points that the ones citizens perform, leading to a higher percentage of walking choices. It reinforces the need for more precise data regarding citizen's mobility behaviors.

The Attractiveness Random Factor model, incorporating stochastic elements to simulate user preferences, performs poorly. This high error rate indicates significant deviations between observed and predicted values across all splits, especially for the Walking split, where the error is notably higher due to the small base value. The large discrepancies suggest that random factors alone are insufficient to accurately model the complexity of real-world decision-making processes.

In contrast, the Logit model demonstrates superior performance with a MAPE of 7.51%. The APEs for Car split, PT split, and Walking split are 1.63%, 6.67%, and 14.23%, respectively, all indicating relatively high accuracy.

It is relevant to highlight that data revealing citizens' choices based on the situation and not just aggregate resulting data would allow for a more complex reflection and evaluation of the results and influences choices.

4.2.7.2 Sensitivity to policy

The primary goal of this model is to integrate it into a larger system for testing various transportation policies. Understanding how these models respond to different infrastructure changes is essential. In this section, we examine the behavior of different modal choice models under varying infrastructure conditions.

We tested all modal choice models against a 10% change in available infrastructure. The results, presented in Table 4.18, reveal several insights. Notably, the Logit modal choice model does not show any change in the percentage of the population choosing cars as their primary mode of transportation when infrastructure changes occur. Specifically, increasing road area and car costs do not influence the agents' choices in the Logit model. In the data studied, the percentage of daily car users is 65.2%, meaning basically all active population. In the model developed, there is the assumption that only the active population has access to cars. The result is that the Logit model over-prioritizes income and becomes insensitive to other changes. This reinforces the need for disaggregated training data to ensure the model assigns appropriate weights to different attributes and does not overly rely on a single factor, such as income.

Conversely, the Greedy implementation of the modal choice model shows expected responses to policy changes. These results should be validated against real-world data to accurately reflect citizens' behaviors and ensure the model's reliability. Considering its performance on the validation and sensitivity analysis tests, this will be the model chosen to integrate the main model.

Table 4.18: Percentage change in modal splits for different policy changes.

Model	Modal Split	Increase Bus Trips	Increase Bus Routes	Increase Rail- way Trips	Decrease Ticket Cost	Increase Road Area	Increase Car Cost
Greedy	Car	-0.9569%	-0.8364%	-0.2584%	-1.1141%	0.7102%	-3.8113%
	Bus	5.0910%	8.5469%	-0.7476%	5.4972%	-1.8239%	8.9988%
	Railway	-4.5276%	-1.2953%	6.0567%	3.8462%	-1.4714%	11.0538%
	Walking	-0.7888%	-5.2373%	-0.0936%	-2.8947%	0.0000%	0.0000%
Attractiveness Factor	Car	-0.7654%	-2.1649%	-0.1575%	-0.2774%	1.0294%	-2.2443%
	Bus	2.6579%	9.9867%	-0.1368%	1.2988%	-0.6255%	1.2889%
	Railway	-0.8231%	-2.2453%	1.8778%	1.4457%	-0.4867%	1.3883%
	Walking	-0.7465%	-3.7210%	-0.1486%	-0.8572%	-0.5612%	1.2106%
Logit	Car	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
	Bus	1.0655%	9.7066%	-0.6981%	0.1945%	0.0000%	0.0000%
	Railway	-1.7950%	-5.9028%	1.1977%	-0.3342%	0.0000%	0.0000%
	Walking	0.0000%	-14.5772%	0.0000%	0.0000%	0.0000%	0.0000%

4.3 Hybrid Model

This section aims to explore the implementation of the Hybrid model. It starts by presenting the feedback loops to highlight the logic behind the relationships between the variables, then it presents the structure, focusing on how the model is organized. It continues by expanding on the transformation of aggregate variables into disaggregate variables and vice-versa. Afterward, the possible policies that policymakers can test on the model are enumerated and explained, and finally, there is the validation of the model.

4.3.1 Feedback Loops

Feedback is the main principle of System Dynamics. It is relevant to explore the main feedback loops in the final model to ensure this principle is respected. In Figure 4.21, the main dynamics of the model are explored. It is a more complex version of the Causal Loop Diagram represented in Figure 4.2, showcasing the added complexity of the modal choice. With the Agent-based modal choice, some of these relationships are less direct. For example, higher income impacts the agent's value of travel time; this, in turn, in the examples explored, turns into a higher modal split for the car as a transportation mode because it is usually the fastest mode. It is not a direct relationship in the model, but in Figure 4.21, there is a direct relationship between these variables. The goal was to showcase a simplified version of the model's behavior and how these variables impact each other. Only the loops added by the inclusion of modal choice will be included in this subsection, but the feedback loops presented in Section 4.1 remain in the final model.

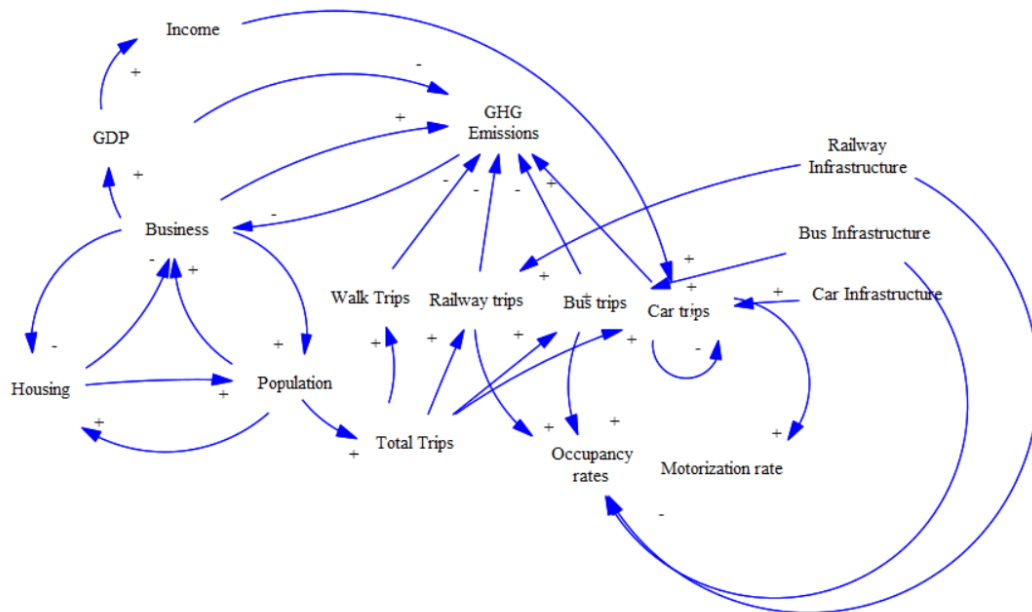


Figure 4.21: Causal Loop Diagram showcasing the main loops.

In Figure 4.22, the feedback loop regarding car trips is displayed. It is employed by the Agent-Based model, meaning if the road capacity does not change, there is a limit to where choosing a car is desirable due to the congestion of the roads. This can be considered a self-correcting feedback loop because more car trips can lead to less car trips.



Figure 4.22: Feedback loop in car trips.

The feedback loop that captures the main subsystems of the model is represented in Figure 4.23. If the population increases, the number of daily trips increases, which may lead to a rise in GHG Emissions that has an impact on the economy, which eventually makes the city less desirable, impacting the population's will to stay. It ends up being a self-correcting feedback loop.



Figure 4.23: Feedback loop uniting the most important elements of the system.

Given that business is connected to various dimensions of the model, there are numerous feedback loops that follow this logic by following the loops associated with business. Another relevant one is presented in Figure 4.24. As previously explained, there is no direct connection in the model between income and car trips. However, the model demonstrates this behavior through the implemented modal choice mechanism, where higher-income agents tend to prioritize travel time when making transportation decisions. Since cars are typically the fastest available mode of transport in most scenarios, these agents are more likely to choose car travel, leading to an increase in car modal share, meaning more trips by this transportation mode. It regards another self-correcting loop, this time regarding Income.



Figure 4.24: Feedback loop regarding income change.

The resulting system is composed of complex interactions between each part of the system. It proves that the principles of System Dynamics can be employed through different methods. The advantages of the approach will be expanded upon. The goal of this section is to provide a view of the interactions in the model developed.

4.3.2 System Architecture

The System Dynamics module was implemented through Vensim, the Agent-Based was implemented in Python, and the integration was implemented through **PySD**, a Python library made for running System Dynamics models in Python, with the purpose of improving integration with more complex methods. The library was used to split the Vensim implementation into subsystems and run each step, meaning a simulated year, articulating them with the Agent-based module.

The Hybrid module serves as a mediator between all the subsystems explored in System Dynamics and the Agent-based modal choice. In Figure 4.25, a component diagram of the model developed is presented. The goal of this diagram is to present the main components that compose the model and how they interact and depend on each other.

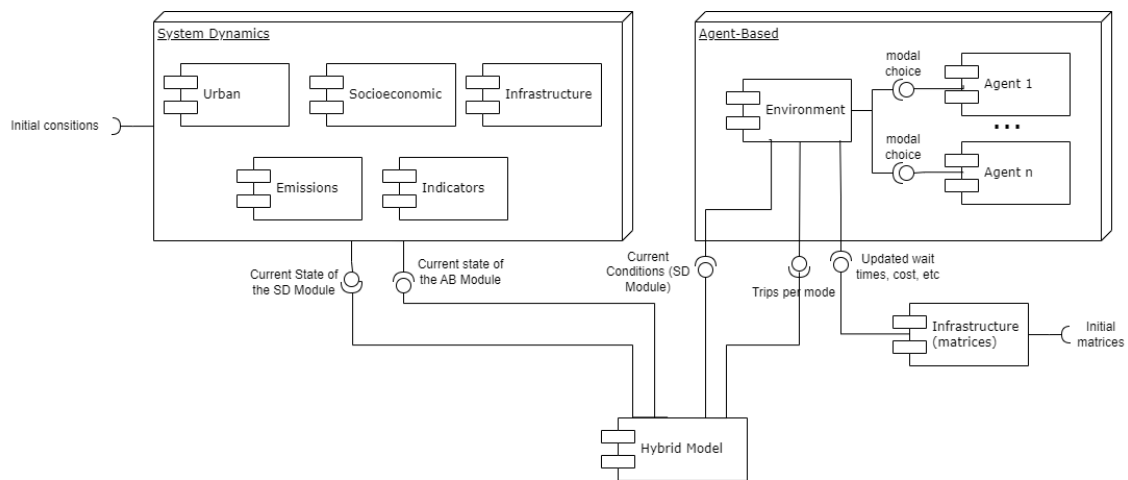


Figure 4.25: Component Diagram of the model developed.

The System Dynamics module defines the conditions of the population and infrastructure. In each step, a year, a new population of agents is created based on the conditions described by the System Dynamics variables. The Agent-based module simulates one typical day of passenger commute and their choices, modeling the population through the conditions described in the current year by the economy and socioeconomic subsystems. This is then extrapolated to the number of trips per year per transportation mode. Emissions and indicators are calculated through results from both the Agent-Based and System Dynamics modules. This communication is managed by the Hybrid Model component as seen on Figure 4.25. The execution of the model is presented in Figure 4.26.

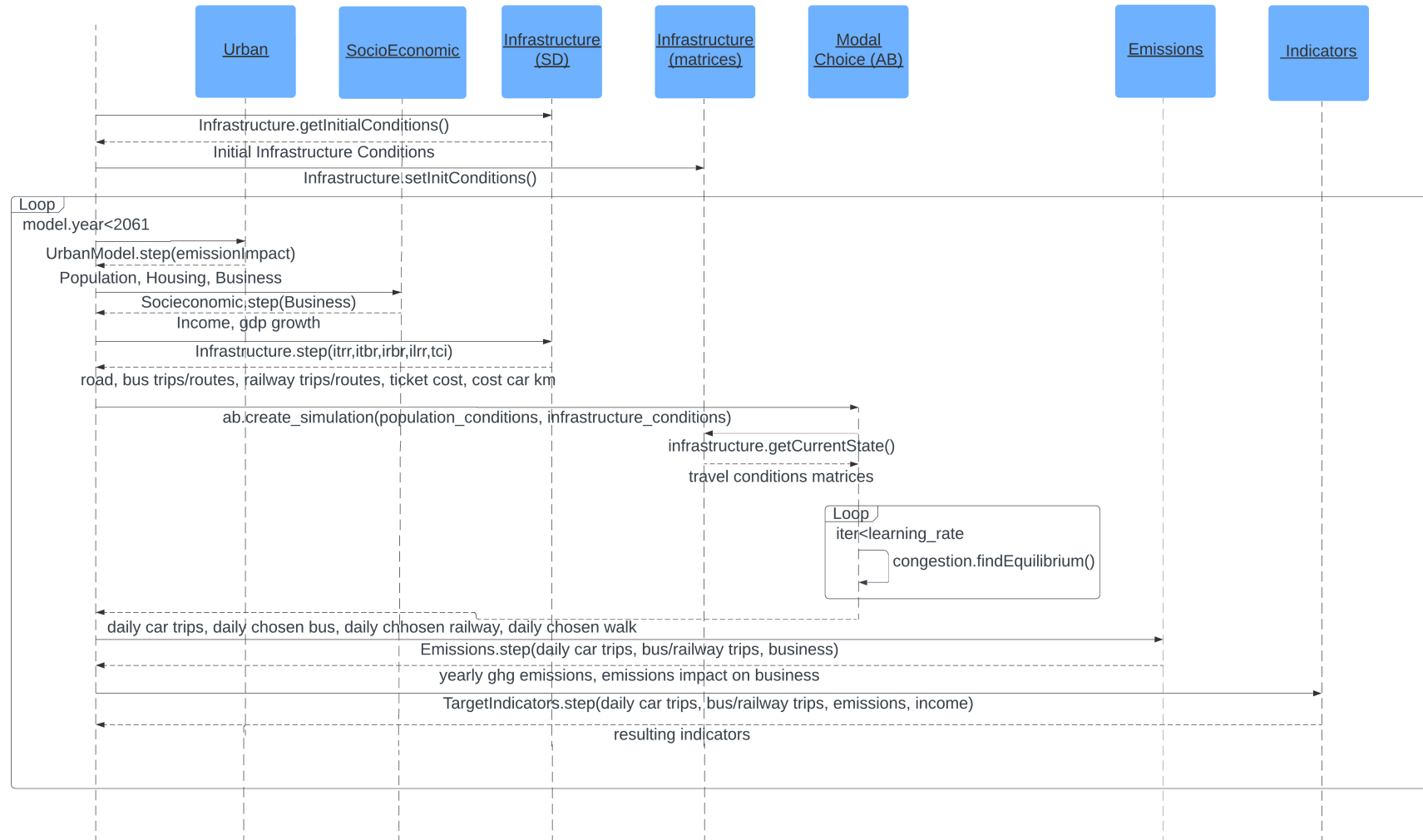


Figure 4.26: Sequence Diagram showcasing the interactions between subsystems.

4.3.3 Interactions between modeling approaches

This subsection aims to explain the variables that impact modal choice and their correspondence in the Agent-Based model. There are three key interactions: Defining the Population, Defining the infrastructure agents react to, and Extrapolating the results to the System Dynamics module and their impact.

4.3.3.1 Creating the Population

The population of agents is created each year, representing its current composition and purchasing power. The Origin-Destination Matrix does not change through time, but the number of trips and transportation mode conditions between OD pairs change. In Table 4.19, the direct effects of each variable are documented.

Table 4.19: Effect of System Dynamics Variables on Agents Population.

System Dynamics Variable	Effect on the Composition of the Agents Population
Population	Generates the number of agents, meaning the number of daily trips. The relationship between population and number of trips was calculated with the information provided by Instituto Nacional de Estadística, I. P. (2018)
LPF (Labor percentage factor)	Generates the percentage of the population that is employed. The agents that are not being assigned a permanent income of 200
Monthly Income 20%	20% of agents in working conditions will be assigned this income
Monthly Income 50%	70% of agents in working conditions will be assigned this income
Monthly Income 90%	10% of agents in working conditions will be assigned this income

4.3.3.2 Infrastructure changes

This subsection aims to explain the representation of infrastructure and how it changes. There was an interest in defining infrastructure because many changes to mobility plans mean investing more or less in providing better conditions for each transportation mode. For practical reasons, infrastructure comprises the aspects that impact travel access, time, and cost.

The definition of infrastructure in the System Dynamics module has been explained in section 4.1.4. To work with the Agent-based implementation, it must express changes to the perceived times and costs in each origin-destination pair. To achieve this, matrices regarding the initial wait times, trip times, road capacities, and trip distance were created. These define the conditions present in the initial infrastructure. All the changes to the infrastructure have proportional changes

to the conditions described. For example:

$$W_{od,m,current} = W_{od,m,initial} \cdot \frac{T_{m,initial}}{T_{m,current}} \quad (4.9)$$

where:

$W_{od,m,current}$ = Current value for an origin-destination pair (od) and a transportation mode (m)

$W_{od,m,initial}$ = Initial value for an origin-destination pair (od) and a transportation mode (m)

$T_{m,initial}$ = Initial time for transportation mode (m)

$T_{m,current}$ = Current time for transportation mode (m)

Trips in Public Transport, in reality, are not distributed equally throughout the day. Infrastructure changes are mainly made through changes to the aggregate variables in System Dynamics. With that in mind, this approach focuses on the perceived wait time in peak hours of the day and how that may change with the increased frequency of the transportation systems.

The System Dynamics variables and their effect in the Agent-based module, consequently modal split, are described below in Table 4.20.

Table 4.20: Effect of System Dynamics Variables on Transportation Conditions perceives by agents

System Dynamics Variable	Effect on the Transportation mode's characteristics
Area of road	Changes to road capacity matrix
Car Cost per KM	Direct representation affects the experienced cost
Number of Trips per Bus Route	Affects the Bus wait time matrix
Number of Bus Routes	Affects the percentage of the population that is considered to have access to Bus (lives within a 1km range of a station)
Number of Trips per Railway line	Affects the Railway wait time matrix
Number of Railway Lines	Affects the percentage of population that is considered to have access to Railway (lives within a 1km range of a station)
Ticket Cost	Affects the cost of choosing a Public Transportation Mode

4.3.3.3 Impact of Agent-Based module on System Dynamics module

In this subsection, the final interaction between these modules is explored. It consists of taking the aggregate results of the number of trips for each transportation mode and including them in the

System Dynamics module so that the final results for that year can be displayed. This interaction is explored in Table 4.21.

Table 4.21: Impact of Agent-Based Results on System Dynamics.

Agent Based Result	Impact on System Dynamics
Daily car trips	• Extrapolated to number of trips per year and used to calculate emissions from private vehicles • Used to calculate motorization rates
Daily Bus Passengers	• Used to calculate occupancy rates, based on the infrastructure described
Daily Railway Passengers	• Used to calculate occupancy rates, based on the infrastructure described
Daily Walk trips	• Does not have a direct impact on the indicators represented

4.3.4 Policy implementation

This section presents the different policies that can be employed in the model.

The main policies are inspired by the models observed. They consist in improving the infrastructure by a certain percentage every 5 years. They indicate changing the aggregate System Dynamics value, which impacts all the values defined by the matrices, meaning the same impact in all the zones. These consist of:

- Add x% more of road .
- Add x% more Bus lines.
- Increase in x% the trips per route for Bus.
- Add x% more Bus lines.
- Increase in x% the trips per route for Railway.
- Add x% more Railway routes.

Adding railway and bus routes means increasing the number of people in a certain zone who have access to that transport mode. Because in some areas, there is no railway access, this measure does not have the desired effect. This is because there was a desire to implement policies through the System Dynamics model, meaning aggregate values, to impact the whole system. To test the

expansion of the railway as a means of transportation between origin-destination pairs where it was not available before, it is necessary to change the time trip and wait time matrices that define these.

Another set of policies can be changing the cost associated with each transportation mode. These policies are also applied every 5 years, such as:

- Increase in x% the Public Transport ticket price.
- Decrease in x% the Public Transport ticket price.
- Increase in x% the cost to ride a car per km.
- Decrease in x% the cost to ride a car per km.

The ticket cost used implies the cost per trip for commuters who have the monthly ticket. The cost of using a car per km includes taxes, initial investment, insurance, and fuel prices, so increasing or decreasing the cost could mean affecting the expected amount required in taxes or the effects of changing fuel costs.

Other policies that don't affect modal choice, so they are not as explored, are affecting the fuel share of the fleet. Currently, the percentage of private vehicles, meaning electric cars, is connected to GDP growth, meaning there is only investment in new cars with economic growth. Implying the percentage of electric vehicles change at a faster or slower rate could exemplify a set of policies' expected results and their effect on the target indicators. Public transport's fuel share does not change at a certain rate, but different values can be set to explore the effect of different fleets, such as:

- Change the growing rate of electric vehicles on the road
- Set different fuel shares for the Public Transportation fleet

Finally, policies that have representation in the model but don't affect the modal split include changing the factors that capture CO₂ in the air, such as increasing green areas and CO₂-capturing technologies.

- Invest in Green area
- Invest in CO₂ capturing technologies

A policy can also mean just a change in the matrices that dictate the conditions for each transport mode between two target points. This technique can be used to explore the expansion of infrastructure to new zones that change the system but not in the same amount in every zone. This type of policy is not as explored because the focus is on aggregate change to the model; despite this, it is still possible and could be explored further.

A policy can mean changing variables that impact the indicators through time. Still, the policies that are explored and have more interest, taking into account the model described, are the

ones that impact modal share. These consist of concrete changes to the infrastructure and see what impact they might have on the indicators of the city, taking into account the behavior of individual agents that react to a changing environment. These will be further explored and showcased when exploring the case studies in which the model can be used.

4.3.5 Validation

This section aims to validate the model against real data. The goal was that all result variables were checked against real data, but it was not always available. Some key elements of the system were selected. The simulation started in 2011, and the system's state for 2021 was checked and compared against real data. The measure chosen was Absolute Percentage Error. The results are in Table 4.22.

Table 4.22: Comparison of Observed Data, Simulated Results, and Absolute Percentage Error (APE) for Different Categories.

Category	Observed Data	Simulated Data	APE (%)
Car split	0.652	0.5446	16.55
Public Transport split	0.227	0.2628	15.79
Walking split	0.111	0.1931	73.96
Income 20	752	562.115443	25.25
Income 50	919	788.326121	14.22
Income 90	3526	3439.228847	2.46
Median income	962	830.709246	13.65
Population	166900	141504.225964	15.22
Business structures	16118	22473.309823	39.43
Housing	74537	74120.645536	0.56
Bus occupancy	0.101	0.091483	9.42
Railway occupancy	0.129	0.185735	43.981
Motorization rate	544	487.115672	10.46
Percentage of electric cars in the fleet	0.02	0.025921	29.61

The data used to run the model is described in Table A.1, whereas Table A.2 presents the data used to validate it. There was a desire to validate further, but the evolution of a city is complicated, and it is difficult to get the specific data necessary. More data is needed to check for each variable represented in the model. The results present a working model, with none of the values being absurd. The error ranges from 0.56% to more than 40% when representing Railway occupancy rates. The highest regarded the walking split, which as an absolute error

would be a 0.08 difference, but given the small value, appears bigger as an absolute percentage error. Getting an accurate view of reality in the many areas that define a city can be complex. The model may not yet be a reliable tool with accurate predictions, but it is believed that the subsystems represented and their interactions provide an interesting view. The subsystems should be expanded and calibrated further to guarantee accurate usability in real-case scenarios. The main focus of the dissertation was on the possibilities added by combining two approaches, further efforts should be employed to ensure a calibrated, reliable model.

Chapter 5

Case studies

This section contains the exploration of the use cases where the model developed can be employed. It focuses on a real case to demonstrate the relevance of its application in recent challenges.

5.1 Setting up the case study for the city of Gondomar, Porto

The main city studied was Gondomar, in the Porto district. The goal is to explore the current mobility conditions of the municipality and the expected results of certain policies. Getting accurate current data is an ongoing challenge in the development of the dissertation. The model was initiated mostly with data from 2021, the last census; the data used is available in Table A.3.

To capture citizens' daily movements, the most detailed data available is provided by a study of Porto and Lisbon mobility in 2017 (*Instituto Nacional de Estatística, I. P., 2018*). INE provided detailed data for the development of this dissertation that indicates the number of trips on an average day between Municipalities, meaning between Porto and Gondomar, or Maia and Gondomar, but not the places within Gondomar. Given the importance of understanding intra-city dynamics, the Origin-Destination Matrix was enhanced with synthetic data. This data was derived from the population counts of each parish in Gondomar as of 2021 (*Instituto Nacional de Estatística, 2023*), allowing for a refined analysis of local travel patterns. So, the matrix describes trips to and from the parishes in Gondomar to other parishes and the main traveled municipalities, namely Maia, Porto, Vila Nova de Gaia, Valongo, and Matosinhos. It ignores the trips made between municipalities that don't include Gondomar. The updated matrix, shown in Table A.4, represents travel fractions rather than absolute numbers. This method maintains the proportionality of trips over the years despite fluctuations in population, adhering to the necessary assumption of constant trip distribution due to the constraints of available data. Additionally, leveraging data from *Instituto Nacional de Estatística, I. P. (2018)*, a table outlining the hourly distribution of trips has been developed. The findings from this analysis are detailed in Table A.5, which applies to all OD pairs in the trip generation model.

There is a desire to capture the mobility infrastructure that agents experience accurately. To capture the conditions available for each OD pair for each transport mode, the following matrices were created:

- Road distance
- Road capacity
- Bus Wait Time
- Railway Trip Time
- Railway Wait Time

As previously described, there is no representation of roads. The model was intentionally designed to contain only information that can be described through matrices. Target points for each location were chosen to develop the Road Distance matrix. Then, through Google Maps, the road distance between each point was calculated and inserted into the matrix. The resulting matrix is available in Table A.6. Similarly, to represent the road capacity between two places, there was an estimation based on [National Academies of Sciences, Engineering, and Medicine; Transportation Research Board \(2022\)](#) and the road type present in the area. The capacity was described in vehicles per hour. The values chosen were 400 vph between parishes and 2000 vph for inter-city trips. The values were estimated based on the roads available because it was necessary for the modeling process, but specialists in the field should review it to ensure accuracy. The final matrix is available in Table A.7.

Regarding public transportation infrastructure, it can be difficult to access older information about the expected lines and waiting times between specific places. With ongoing changes to the company most present in the city, Gondomarense, which was turned into UNIR, and the presence of multiple Bus companies, getting these was especially a challenge. To simplify the process, it was assumed that the current conditions available are able to represent the public transportation conditions experienced in 2021. The Bus Wait Time Matrix was developed by looking at the time in between bus departures in peak hours that perform the trip from one target point to another in the OD pair. Waiting time was defined as the interval between departures divided by 2. When more than one bus trip was necessary, these times were summed up. The Bus Wait Time matrix is available in Table A.8. Then, it is assumed the distance between the points is the same as described in the road matrix. This is a simplification, given that public transport may employ longer routes.

The railway infrastructure included both Metro do Porto and Urban Trains from Comboios de Portugal. The matrix for Railway Trip Time was calculated directly by looking at the predicted times available. When there is no railway connection for an OD pair, the predicted time is infinite, which ensures this option never gets chosen. The process for creating the Railway Wait Time matrix was similar to the one described for buses. The results are available in Table A.9 and Table A.10, respectively.

Other infrastructure conditions are the cost of using a car each km for Portugal and public transport ticket costs. Because the model is supposed to be generalizable for a typical day of the year, the ticket cost chosen was the monthly ticket divided by 60, typically two trips a day. This means a public transport choice would be the main transportation choice for the agent performing that trip. All the sources for the values used are available in Table A.3.

There was a difficulty in getting the accurate values for all variables represented in the equation regarding greenhouse gas emissions. To combat it, there were example vehicles chosen for each fuel category. There was a focus on getting the full emissions in the case of electricity, meaning accounting for the emissions associated with electricity production. These values are also available in Table A.3.

The goal was to get a descriptive view of the mobility system and how it is perceived by the citizens with the limited data available. This view could be further developed given more accurate and recent data.

5.2 Case study - Gondomar Main policies

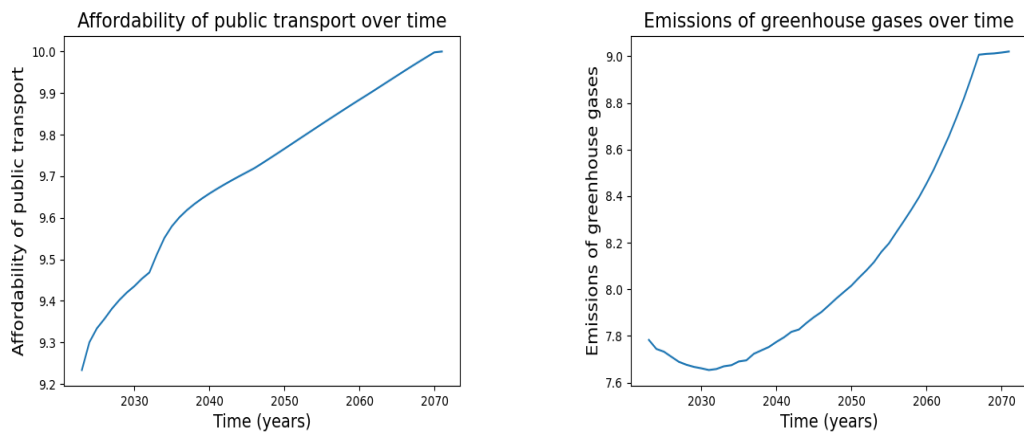
The goal of this section is to explore the indicators' results over the years for each policy. It is also interesting to explore how each policy impacts the travel behaviors of different income groups. It will start by presenting the model predictions with no changes to the infrastructure, and then it will present the effects of each policy that consists of the variable being increased 5% every 5 years, comparing it to the no changes scenarios.

5.2.1 Business as Usual

In the case of no infrastructure changes, the following graphs present the predicted evolution of Gondomar indicators. The goal is to then compare it with the various policy implementations.

The document that inspired the project development assigns values from 0 to 10 to the main indicators. In Figure 5.1a, it is possible to view the predicted evolution of public transport affordability. This indicates that there is already a high level of affordability if citizens acquire the monthly pass. The score grows because while the ticket cost remains the same, the predicted income level increases. In the case of the emission of greenhouse gases, represented in Figure 5.1b, it is also expected to rise due to the projected change in the fleet to more electric cars. Mobility usage is not explored because even though it is represented in the model, there is not enough accurate data available.

Further information about the indicators is available in figures 5.2a, 5.2a and 5.3. The population of Gondomar has decreased in the year 2021 when this simulation begins. Even if the decrease is circumstantial, the model assumes the population decreases in the first few years, meaning a smaller number of cars occupying the road, less congestion, and more likelihood of choosing car trips, as seen in Table 5.1. This phenomenon can explain the motorization rate observed in Figure 5.3.



(a) Affordability of public transport to the poorest group with no infrastructure changes. (b) Emissions of Greenhouse Gases with no infrastructure changes.

Figure 5.1: Results of the simulation on the main indicators.

Table 5.1: Transportation Mode Splits from 2021 to 2071.

Year	Car Split (%)	Bus Split (%)	Railway Split (%)	Walking Split (%)
2021	58.59	15.70	4.14	21.57
2026	59.76	14.95	3.83	21.45
2031	60.21	14.67	3.77	21.34
2036	59.97	14.71	3.82	21.50
2041	59.59	15.02	3.88	21.51
2046	59.17	15.40	3.92	21.51
2051	58.86	15.63	4.00	21.51
2056	58.43	15.97	4.06	21.54
2061	58.16	16.19	4.14	21.51
2066	57.98	16.38	4.17	21.46
2071	57.98	16.38	4.17	21.46

In Table 5.2, the modal split per income group can be observed. In non-active agents, there is no access to a car, and the high percentage of walking choices might indicate a lot of the citizens are not within the acceptable range of public transportation. In the other groups, car dominates the modal share, especially high income, where it is consistently above 90%.

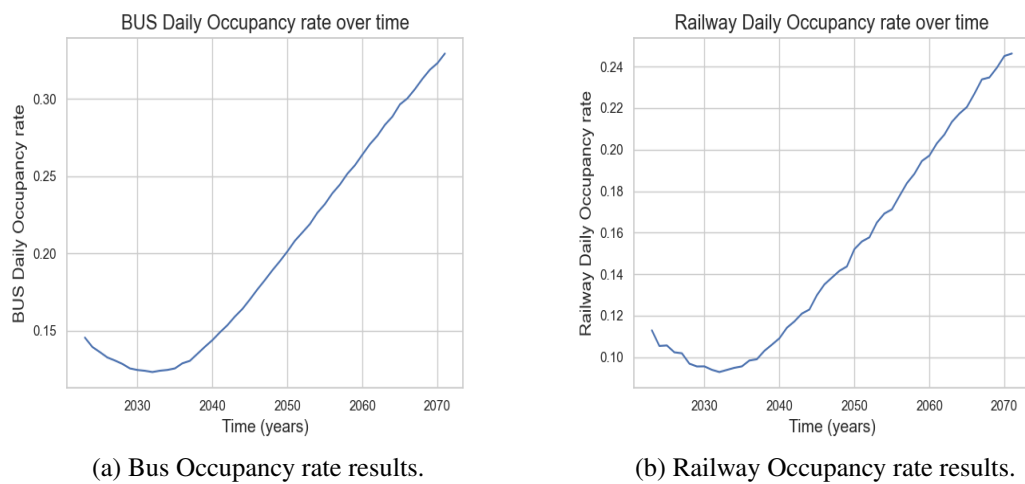


Figure 5.2: Results of the simulation with no infrastructure changes.

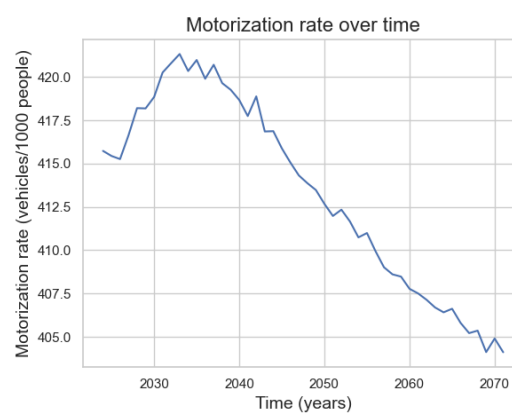


Figure 5.3: Motorization rate from 2021 to 2071 with no infrastructure changes.

Table 5.2: Modal split change over time across different income groups and modes of transport for business as usual scenario.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.0	27.20	8.79	64.01	82.08	14.80	3.11	0.0	90.77	8.06	1.17	0.0	98.39	1.52	0.09	0.0
2031	0.0	27.73	8.74	63.53	83.56	13.96	2.48	0.0	91.49	7.41	1.11	0.0	98.27	1.64	0.09	0.0
2036	0.0	27.67	8.84	63.49	84.53	13.20	2.26	0.0	91.43	7.46	1.11	0.0	98.28	1.66	0.06	0.0
2041	0.0	27.53	8.90	63.58	84.36	13.16	2.48	0.0	90.75	8.07	1.18	0.0	97.83	2.09	0.09	0.0
2046	0.0	27.51	9.02	63.47	84.35	13.30	2.34	0.0	90.02	8.71	1.28	0.0	97.47	2.37	0.16	0.0
2051	0.0	27.65	8.85	63.50	84.06	13.61	2.33	0.0	89.35	9.24	1.41	0.0	96.71	3.00	0.28	0.0
2056	0.0	27.63	8.71	63.66	84.30	13.26	2.44	0.0	88.64	9.80	1.56	0.0	96.08	3.60	0.32	0.0
2061	0.0	27.54	8.77	63.69	84.41	13.23	2.37	0.0	87.95	10.32	1.73	0.0	95.59	4.02	0.40	0.0
2066	0.0	27.35	8.80	63.86	84.65	13.04	2.31	0.0	87.36	10.78	1.87	0.0	94.95	4.56	0.49	0.0
2071	0.0	27.74	8.72	63.54	85.08	12.66	2.26	0.0	87.04	11.01	1.96	0.0	94.49	4.99	0.51	0.0

These correspond to the conditions observed if no changes are made to the infrastructure, so they are influenced mostly by the evolution of the population from the Urban Model. The goal is to now compare them to the policies and explore their effectiveness.

5.2.2 Increase the number of Bus Trips per Route

This policy consists of increasing in 5% every 5 years the average number of trips per route, meaning agents encounter smaller wait times when assessing the cost of a bus trip.

It is relevant to first observe how the policy affects modal split since it is the variable that impacts everything else. To avoid confusion added by the changes in the population through the years, the values will be interpreted as the fraction of trips made with each mode. In Figure 5.4, it is possible to compare the modal split to the Business as Usual scenario. There is a great change, especially in the car and bus shares. It is also possible to observe that after some years, the modal share begins to stabilize, meaning changing the frequency of buses no longer has any effect on the response of the citizens, being from the point of view of modal choice alone, not accounting for bus capacity, unnecessary.

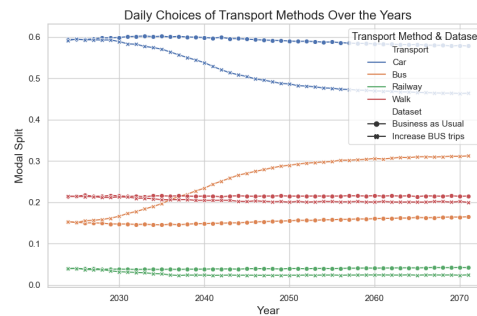


Figure 5.4: Change in modal choice with increased bus trips vs. business as usual.

In Table, 5.3, the difference between the Modal Split percentage of the business as usual and increased bus trips per route scenarios are presented. The low and medium income present bigger changes in percentages, almost getting to 20%. This could mean these groups have a higher response to policies that affect a trip's time. The change in the high-income population, even if not as accentuated, is still relevant as this is a population that is not prone to use public transport at all, and the share more than doubled when compared to the scenario with no alterations to the infrastructure.

Table 5.3: Change in modal choice per income group with increased bus trips vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.00	1.04	-0.45	-0.58	-0.20	0.30	-0.10	0.00	-0.30	0.31	-0.18	0.00	-0.43	0.44	-0.01	0.00
2031	0.00	2.89	-1.89	-1.00	-2.19	2.35	-0.16	0.00	-2.49	2.54	-0.05	0.00	-0.19	0.23	-0.04	0.00
2036	0.00	6.03	-3.61	-2.42	-7.10	7.73	-0.62	0.00	-5.95	6.14	-0.19	0.00	-0.94	0.95	-0.01	0.00
2041	0.00	6.85	-3.74	-3.12	-12.47	13.64	-1.17	0.00	-10.83	11.14	-0.32	0.00	-2.54	2.56	-0.02	0.00
2046	0.00	7.27	-3.86	-3.41	-16.39	17.41	-1.02	0.00	-15.06	15.43	-0.37	0.00	-4.67	4.76	-0.09	0.00
2051	0.00	7.56	-3.65	-3.90	-17.37	18.42	-1.05	0.00	-17.28	17.77	-0.49	0.00	-5.34	5.53	-0.19	0.00
2056	0.00	7.87	-3.56	-4.30	-18.75	19.95	-1.20	0.00	-17.92	18.50	-0.59	0.00	-6.16	6.38	-0.21	0.00
2061	0.00	7.56	-3.55	-4.01	-18.68	19.71	-1.03	0.00	-18.14	18.85	-0.71	0.00	-6.82	7.07	-0.25	0.00
2066	0.00	8.06	-3.56	-4.49	-18.78	19.87	-1.09	0.00	-18.41	19.21	-0.80	0.00	-7.33	7.71	-0.38	0.00
2071	0.00	7.53	-3.50	-4.03	-19.09	20.11	-1.01	0.00	-18.55	19.42	-0.87	0.00	-7.59	7.96	-0.36	0.00

Regarding occupancy rates, in Figure 5.5, it is possible to observe that it continuously rises through the years. It is important to remember the projected major growth in population that explains the overall growth in occupation rate. But when compared to the business-as-usual scenario, it is possible to see that even though there is an increase in the offer available, meaning more buses and more seats, the response to it justifies it. It suggests that the current occupation rates can correspond to low adherence due to a lack of proper frequency that addresses citizens' needs and that there is space and projected response to changes.

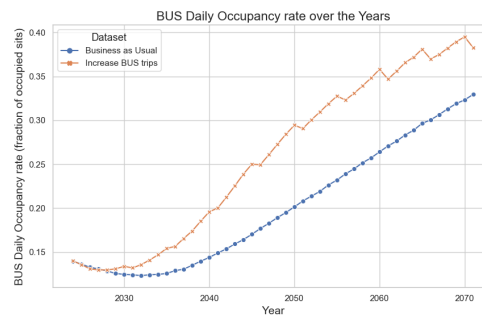
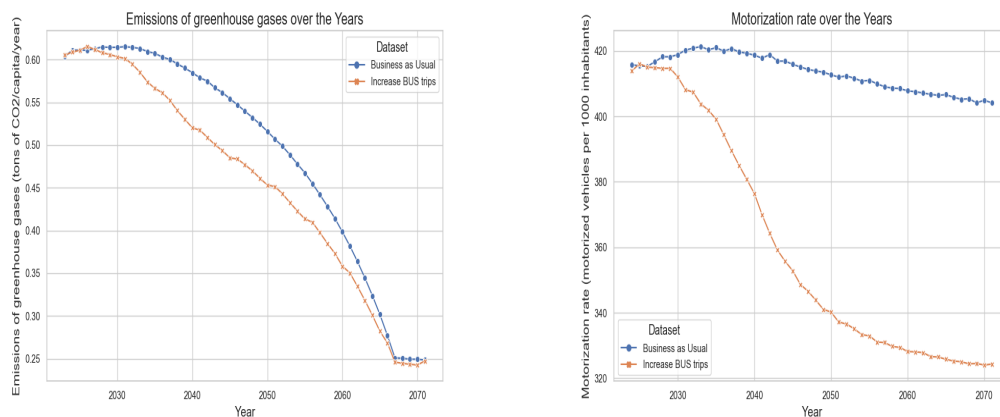


Figure 5.5: Comparison of business as usual and increase bus trips in the yearly bus occupancy rates.

The emissions of greenhouse gases are projected to decrease faster in closer years, but the main component affecting it seems to still be the electrification of the fleet. These results can be observed in Figure 5.6a. The motorization rate would drop relatively fast, given the change in modal split observed. It would eventually start stabilizing as the citizens no longer respond to more bus frequency as predicted. These results can be observed in Figure 5.6b.



(a) Yearly emissions per capita.

(b) Yearly Motorization rates.

Figure 5.6: Comparison of business as usual and increase bus trips results.

5.2.3 Increase Bus Lines

The next policy being evaluated is to increase bus lines. This affects the percentage of the population that effectively has access to this transportation mode.

With this policy, the main affected splits correspond to bus and walking, as opposed to the previous, which affected car splits significantly. These results can be observed in Figure 5.7. It can be further validated through Table 5.4. The policy mainly affects the nonactive population that did not have access to buses, meaning they did not live within one km of a station. In the other changes to the other groups are merely residual and can be attributed to the changes in the population distribution on each run.

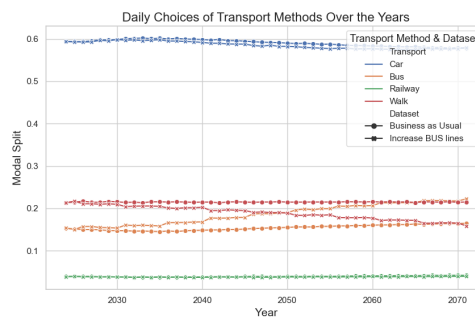


Figure 5.7: Change in modal choice with increased bus lines vs. business as usual.

Contrasting with the other policy, the bus occupancy rate, represented in Figure 5.8, remains lower than the observed in the business-as-usual scenario. This can be attributed to a high increase in the offer. Each new line would get the same number of trips as defined in the average, but not as high of a response when compared to the other policies' effect, as observed in the Tables mentioned. The same can be attributed to the emission of greenhouse gases and motorization rates, available in Figures 5.9a and 5.9b respectively, because the policy does not affect the number of cars on the road directly it ends up having little effect on the target indicators when compared to the previous policy.

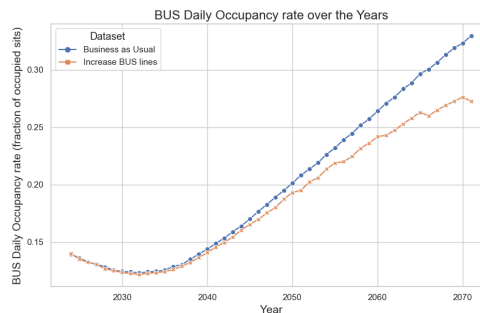
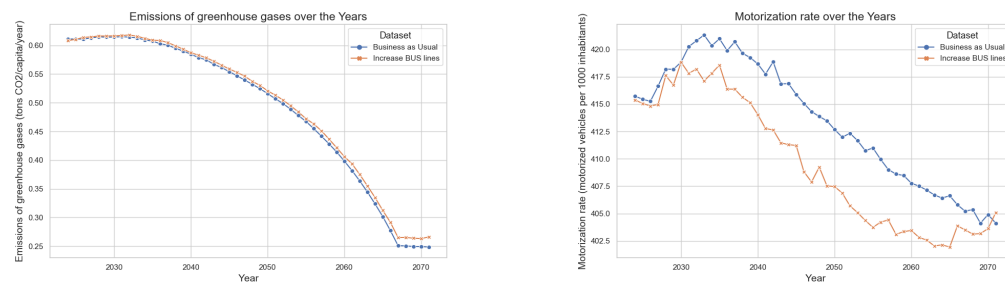


Figure 5.8: Comparison of business as usual and increase bus lines in the yearly bus occupancy rates.

Table 5.4: Change in modal choice per income group with increased bus lines vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.00	1.76	-0.12	-1.64	-0.24	0.23	0.01	0.00	-0.26	0.25	0.01	0.00	-0.07	0.10	-0.03	0.00
2031	0.00	2.88	-0.05	-2.83	-0.95	0.69	0.26	0.00	-0.61	0.59	0.01	0.00	0.05	-0.04	-0.01	0.00
2036	0.00	4.19	-0.21	-3.98	-1.60	1.47	0.13	0.00	-0.76	0.76	0.01	0.00	-0.08	0.10	-0.02	0.00
2041	0.00	6.13	-0.27	-5.86	-2.13	2.40	-0.27	0.00	-0.93	0.93	-0.00	0.00	0.22	-0.22	0.00	0.00
2046	0.00	7.53	-0.41	-7.12	-2.89	3.07	-0.17	0.00	-1.00	1.04	-0.04	0.00	0.12	-0.10	-0.02	0.00
2051	0.00	9.28	-0.36	-8.92	-2.65	2.75	-0.10	0.00	-1.18	1.17	0.00	0.00	0.27	-0.19	-0.08	0.00
2056	0.00	11.35	-0.43	-10.92	-2.74	3.01	-0.27	0.00	-1.06	1.08	-0.02	0.00	1.07	-0.99	-0.07	0.00
2061	0.00	13.23	-0.42	-12.80	-2.65	2.79	-0.15	0.00	-1.01	1.10	-0.08	0.00	1.19	-1.03	-0.16	0.00
2066	0.00	15.41	-0.53	-14.88	-1.98	2.04	-0.06	0.00	-0.30	0.45	-0.15	0.00	1.88	-1.79	-0.09	0.00
2071	0.00	17.14	-0.46	-16.69	-1.11	1.12	-0.00	0.00	0.28	-0.17	-0.11	0.00	2.59	-2.49	-0.10	0.00



(a) Comparison of business as usual and increase bus trips in the yearly emissions per capita.
 (b) Comparison of business as usual and increase bus lines in the yearly Motorization rates.

Figure 5.9: Comparison of business as usual and increase bus lines results.

5.2.4 Increase Railway Trips

As explained, these policies affect the values derived from the original matrices. If there is no railway connection between an OD pair, the policy to increase railway lines does not have an effect on that area. This is the reason this policy is not explored in this section. Increasing railway trips consists in changing the number of trips per line, meaning a higher frequency of railway. Modal split is not as affected as other policies. As it is possible to observe in Figure 5.10, the growth in railway share is not substantial. This is reinforced by the results available in Table 5.5. The policy mainly influences the decisions of low income population. This can be attributed to the frequency of the railway already being high with low wait times, as in the case of Metro do Porto. The main limitation of this transportation method is that it is not available to most OD pairs in Gondomar. It is also relevant to recall that due to the limitation of only one transportation mode per trip, the population that does not live close to a metro stop but gets there by bus or car is not represented.

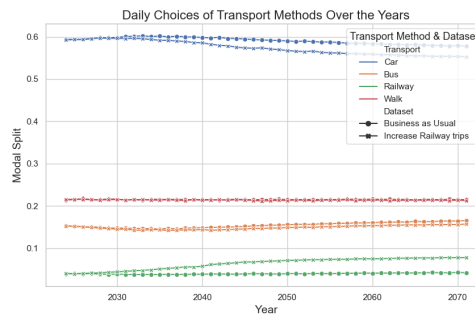
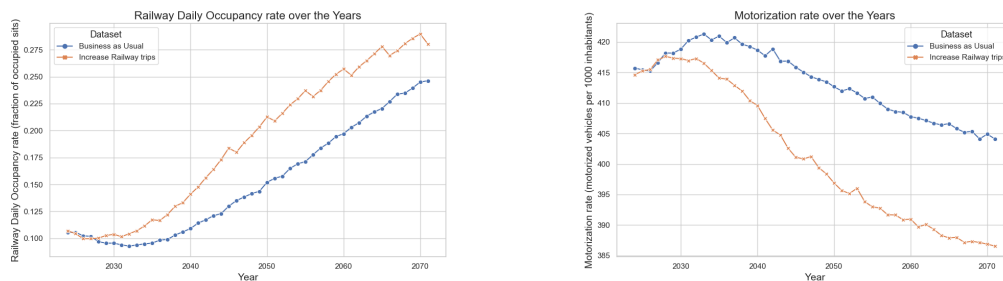


Figure 5.10: Change in modal choice with increased railway trips vs. business as usual.

Figure 5.11a demonstrates that the occupancy rate of railway does raise, especially given the increment in population. As expected and as it is possible to observe in Figure 5.11b, there is the impact on motorization, but it is not as relevant as other policies. Due to this, the effect on the emission of greenhouse gases also ends up being marginal.



(a) Comparison of business as usual and increase railway trips in the yearly Motorization rates. (b) Comparison of business as usual and increase bus lines in the yearly Motorization rates.

Figure 5.11: Comparison of business as usual and increase railway trips results.

Table 5.5: Change in modal choice per income group with increased railway trips vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.00	0.36	0.08	-0.45	0.22	-0.46	0.24	0.00	0.02	-0.07	0.05	0.00	-0.13	0.13	0.00	0.00
2031	0.00	-0.59	0.91	-0.32	-0.40	-1.05	1.45	0.00	-0.56	0.11	0.44	0.00	-0.04	-0.12	0.16	0.00
2036	0.00	-1.11	1.28	-0.17	-1.94	-0.94	2.88	0.00	-1.20	-0.03	1.23	0.00	-0.50	0.08	0.42	0.00
2041	0.00	-1.00	1.23	-0.23	-3.21	-0.96	4.17	0.00	-2.15	-0.42	2.57	0.00	-0.47	-0.51	0.98	0.00
2046	0.00	-0.76	1.22	-0.46	-4.35	-0.85	5.20	0.00	-2.98	-0.42	3.40	0.00	-1.32	-0.10	1.42	0.00
2051	0.00	-1.02	1.43	-0.41	-4.71	-0.92	5.63	0.00	-3.36	-0.58	3.94	0.00	-1.45	-0.33	1.78	0.00
2056	0.00	-0.88	1.51	-0.63	-4.82	-0.68	5.50	0.00	-3.51	-0.73	4.24	0.00	-1.44	-0.62	2.05	0.00
2061	0.00	-0.98	1.44	-0.47	-4.71	-0.86	5.57	0.00	-3.76	-0.62	4.38	0.00	-1.81	-0.41	2.22	0.00
2066	0.00	-0.78	1.49	-0.71	-4.46	-1.08	5.54	0.00	-3.88	-0.67	4.55	0.00	-2.02	-0.54	2.56	0.00
2071	0.00	-1.09	1.58	-0.50	-4.84	-0.56	5.40	0.00	-4.02	-0.64	4.66	0.00	-2.23	-0.41	2.64	0.00

5.2.5 Increase Road Area

In the representation of the road, there is an emphasis on congestion, meaning the direct impact is increasing the road capacity agents face. The results of the policy include, as expected, an increase in car split, taking mainly from the bus option. This can be observed in Figure 5.12. The non-active population does not have access to cars, and low-income and medium-income groups reacted well to the policy, surpassing a 10% change. The high-income group did not have such a creation, but it is mostly due to the fact that most of the group uses cars daily. The share of car usage was already incredibly high and reached the peak of 100% in 2046. These results are available in Table 5.6.

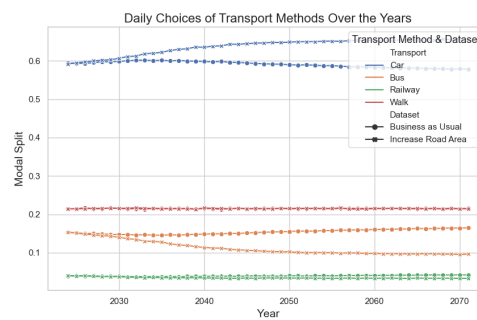
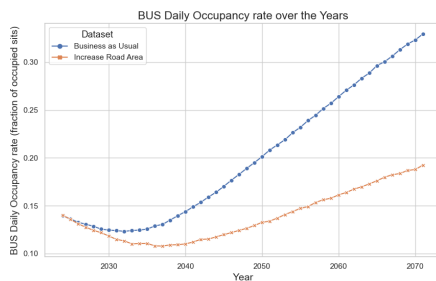


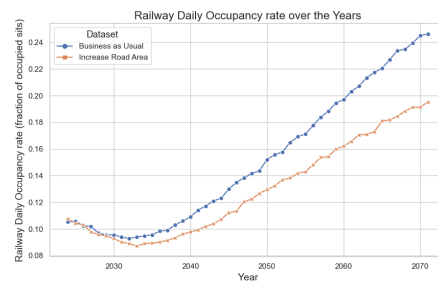
Figure 5.12: Change in modal choice when increasing road area when compared to keeping business as usual.

The occupation rates are set to behave as expected with the observed drop in public transport ridership while public transportation conditions remain the same. These results can be observed in Figure 5.13a and Figure 5.13b. The motorization rate is projected to grow but stabilize since not all the population can get a car; this can be viewed in Figure 5.14a. The effect of the change in the emissions can be observed, but once again, the projected change in vehicle fleet has more of an end effect on the overall emissions projected, Figure 5.14b

Figure 5.13: Comparison of business as usual and increase road area results.



(a) Yearly bus occupancy rates

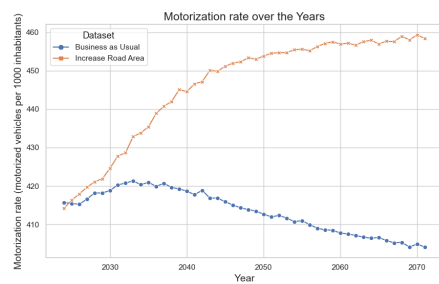


(b) Yearly railway occupancy rates

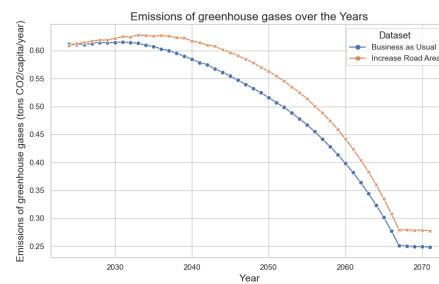
Table 5.6: Change in modal choice per income group with increased road area vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.00	0.20	0.15	-0.34	0.55	-0.59	0.04	0.00	0.34	-0.32	-0.03	0.00	-0.02	0.04	-0.01	0.00
2031	0.00	-0.20	-0.01	0.20	2.99	-2.42	-0.57	0.00	1.67	-1.48	-0.19	0.00	0.88	-0.81	-0.07	0.00
2036	0.00	-0.21	-0.04	0.25	5.36	-4.44	-0.92	0.00	3.79	-3.42	-0.36	0.00	1.40	-1.34	-0.06	0.00
2041	0.00	-0.01	-0.17	0.18	8.39	-6.94	-1.46	0.00	6.25	-5.71	-0.54	0.00	2.13	-2.04	-0.09	0.00
2046	0.00	0.17	-0.38	0.21	10.63	-9.12	-1.52	0.00	8.03	-7.38	-0.65	0.00	2.53	-2.37	-0.16	0.00
2051	0.00	-0.26	-0.03	0.29	12.30	-10.70	-1.60	0.00	9.14	-8.37	-0.77	0.00	3.29	-3.00	-0.28	0.00
2056	0.00	-0.21	0.00	0.21	12.76	-11.01	-1.75	0.00	10.06	-9.14	-0.92	0.00	3.92	-3.60	-0.32	0.00
2061	0.00	-0.07	0.03	0.04	13.28	-11.55	-1.73	0.00	10.89	-9.79	-1.10	0.00	4.41	-4.02	-0.40	0.00
2066	0.00	0.33	-0.01	-0.32	13.60	-11.95	-1.65	0.00	11.53	-10.29	-1.25	0.00	5.05	-4.56	-0.49	0.00
2071	0.00	-0.07	0.00	0.07	13.45	-11.87	-1.58	0.00	11.93	-10.59	-1.33	0.00	5.51	-4.99	-0.51	0.00

Figure 5.14: Comparison of business as usual and increase road area results.



(a) Yearly Motorization rates.



(b) Yearly emissions per capita.

5.2.6 Decrease Public Transport Ticket Cost

As previously explained, an example of policy includes changing the monetary values associated with transportation; change in public transport cost is an example of this. Ticket cost is already considered affordable in the standards defined by **World Business Council for Sustainable Development (2015)**. With this policy and the projected income growth, as expected, the indicator will get to 10 in fewer years. The comparison with business as usual is available in Figure 5.15.

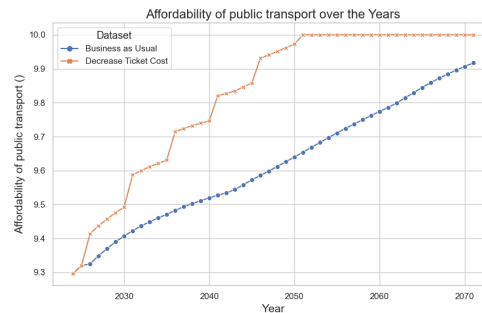


Figure 5.15: Comparison of business as usual and decrease ticket cost on indicator Affordability of Public Transport.

As it is possible to observe in Figure 5.16, the effects of this policy mainly affect the choice between walking and using public buses, with the change in railway usage being minimal. Analyzing Table 5.7, it is possible to observe that the policy mainly has an effect on the non-active portion of the population; it can provide access to the buses. As expected, there are minor changes to the high-income portion; since the initial price is not prohibitive, the main changes that affect these are the expected time. Since the main changes are from the part of the population that would choose walking, few changes to the remaining indicators will be observed.

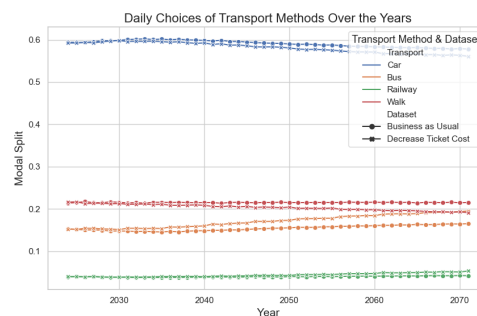


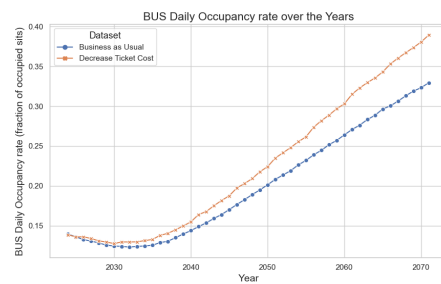
Figure 5.16: Change in modal choice with decreased ticket cost vs. business as usual.

It is possible to observe that changes to the occupancy rates are not as significant as other policies. Railway and Occupancy rates are available in Figure 5.17a and Figure 5.17b. As explained, the changes to the other indicators are not very relevant as the policy does not decrease the number of cars on the road therefore, the graphs will not be displayed.

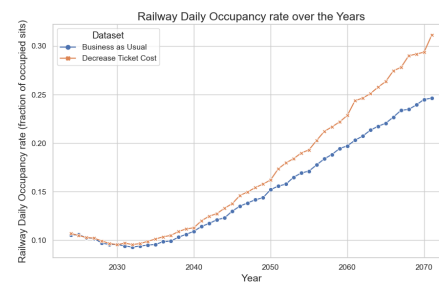
Table 5.7: Change in modal choice per income group with decreased public transport cost vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.0	0.86	0.09	-0.94	-0.58	0.53	0.04	0.0	-0.14	0.14	-0.00	0.0	-0.15	0.17	-0.02	0.0
2031	0.0	1.13	0.11	-1.24	-0.40	0.24	0.16	0.0	-0.59	0.49	0.11	0.0	0.05	-0.01	-0.04	0.0
2036	0.0	1.77	0.17	-1.94	-1.62	0.97	0.65	0.0	-0.79	0.67	0.12	0.0	0.08	-0.07	-0.01	0.0
2041	0.0	2.59	0.14	-2.72	-1.86	1.55	0.31	0.0	-1.13	0.90	0.23	0.0	0.03	-0.03	0.00	0.0
2046	0.0	3.02	0.29	-3.31	-2.49	1.90	0.59	0.0	-1.43	1.12	0.31	0.0	0.02	0.01	-0.03	0.0
2051	0.0	3.59	0.46	-4.05	-2.49	1.65	0.84	0.0	-1.66	1.23	0.42	0.0	0.15	-0.04	-0.11	0.0
2056	0.0	4.09	0.72	-4.81	-2.97	2.19	0.78	0.0	-1.82	1.35	0.47	0.0	0.07	-0.07	-0.00	0.0
2061	0.0	4.55	1.25	-5.81	-3.32	2.33	0.99	0.0	-2.21	1.65	0.56	0.0	0.11	-0.10	-0.01	0.0
2066	0.0	5.11	1.37	-6.48	-3.31	2.33	0.98	0.0	-2.34	1.73	0.61	0.0	-0.01	0.05	-0.04	0.0
2071	0.0	5.18	1.79	-6.97	-3.54	2.40	1.13	0.0	-2.81	2.04	0.77	0.0	-0.08	0.04	0.05	0.0

Figure 5.17: Comparison of business as usual and decrease public transport ticket cost results.



(a) Yearly bus occupancy rates



(b) Yearly railway occupancy rates

5.2.7 Increasing car usage cost

Car cost in the model is meant to include the cost of investment, fuel, taxes, etc. This policy does not specify which is changed; it is just that there is a change perceived by the agents.

The effects of the policy consist of a major decrease in car usage and an increase in public transport usage, both bus and railway. It does not have an impact on walking because most of the citizens walking are non-active, meaning they do not have access to a car, so they are little to no affected by this policy. The modal split change is available in Figure 5.18. These results are reinforced by the values observed in Table 5.8. The policy has a lot of influence on the choices made by low-income and medium-income groups, surpassing 10% difference between business as usual and this scenario. High-income lack of response might be again due to them being more affected by what impacts the time a trip might take than the cost associated with it.

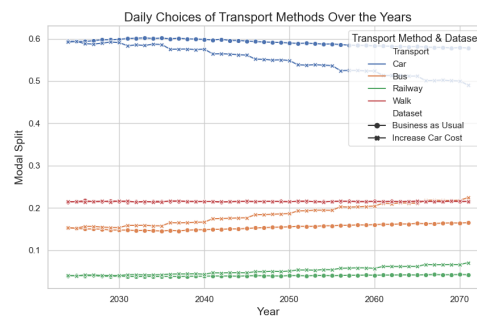
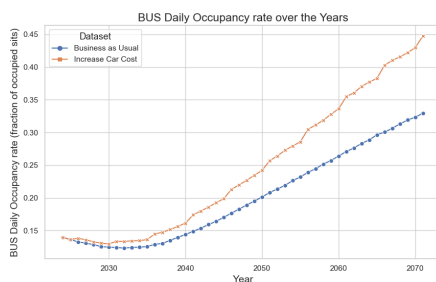


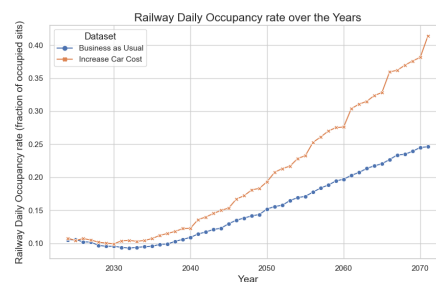
Figure 5.18: Change in modal choice with increased car usage cost vs. business as usual.

There are clear changes in the occupation rates available in Figure 5.19a and Figure 5.19b. The high rise in railway usage can be highlighted as an unexpected change since this was the policy that had the most influence on the transportation mode usage.

Figure 5.19: Comparison of business as usual and increased car usage cost results.



(a) Yearly bus occupancy rates.



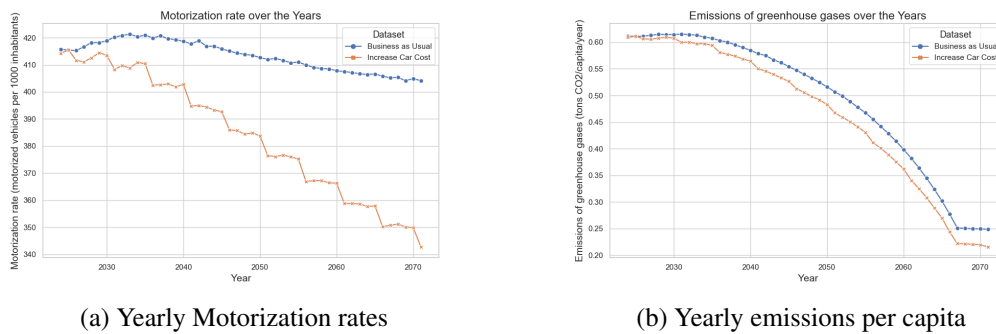
(b) Yearly railway occupancy rates.

Table 5.8: Change in modal choice per income group with increased car usage cost vs. business as usual.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2026	0.0	0.47	0.01	-0.48	-1.55	0.60	0.94	0.0	-1.04	0.89	0.15	0.0	-0.06	0.06	-0.01	0.0
2031	0.0	-0.24	0.18	0.06	-3.22	1.83	1.40	0.0	-2.27	1.98	0.29	0.0	0.13	-0.12	-0.01	0.0
2036	0.0	-0.26	-0.04	0.30	-5.91	3.82	2.09	0.0	-3.50	2.94	0.56	0.0	-0.31	0.30	0.01	0.0
2041	0.0	0.06	-0.10	0.04	-7.98	5.21	2.77	0.0	-4.72	3.85	0.87	0.0	-0.08	0.02	0.06	0.0
2046	0.0	0.06	-0.30	0.24	-9.89	6.39	3.50	0.0	-6.12	4.88	1.24	0.0	-0.26	0.17	0.08	0.0
2051	0.0	-0.29	-0.03	0.32	-11.12	7.33	3.78	0.0	-7.77	5.95	1.82	0.0	-0.10	0.19	-0.09	0.0
2056	0.0	-0.00	0.01	-0.00	-12.24	7.85	4.39	0.0	-9.52	7.13	2.39	0.0	-0.50	0.45	0.05	0.0
2061	0.0	0.13	0.05	-0.18	-14.26	9.34	4.93	0.0	-10.90	7.96	2.93	0.0	-0.45	0.33	0.12	0.0
2066	0.0	0.20	0.06	-0.26	-15.04	9.65	5.39	0.0	-12.62	8.97	3.66	0.0	-0.42	0.33	0.09	0.0
2071	0.0	-0.25	0.08	0.17	-16.56	10.54	6.02	0.0	-14.24	9.89	4.36	0.0	-0.59	0.42	0.17	0.0

The policy also has a high impact on the predicted motorization rate and how it changes. This can be observed in Figure 5.20a. As in previous examples, there is an effect on the emissions per capita but the main determinant on the behaviour of the graph is the change on the composition of the fleet. These results are displayed in Figure 5.20b.

Figure 5.20: Comparison of business as usual and increased car usage cost results.



5.2.8 Conclusions

From the data presented, it is possible to understand what policies are predicted to have a more direct effect on the modal split change and the change in the target indicators. In this case, increasing bus trips and changing car usage costs seem to be the most effective. It is possible to conclude that to have a real impact on the indicator's values, it is relevant to tackle groups that use private vehicles. Policies should be combined to have a fair change in the system and get major changes in the resulting indicators.

There is data on how each group reacts to the policies and how to target specific groups of people given the current available infrastructure and conditions of the population. Non-active groups react the most to increasing bus lines, as they are a key group in public transport usage, but this is not always available. Low-income and Medium-income groups react the most to increased bus trips, changes in road capacity, and car costs. High-income people are the group that least reacts to changes in the infrastructure, according to the choice model chosen, and the policy that has the biggest effect is increasing the number of bus trips, meaning changing the expected time of a bus trip.

The minor changes associated with the railway share are due to only a few OD pairs being covered by this transportation mode. To tackle change in this transportation mode, there needs to be a change in the input matrices.

The response in each OD pair to the policies available has not been studied. Even though the change is equal across all OD pairs information, some citizens might be in more need of the change to use public transport. This data is available, but due to time constraints, the focus was on income groups and not OD pairs. Getting accurate information on the income distribution across OD pairs would also allow for a more credible prediction of future outcomes and reactions to change.

5.3 Case study - New Gondomar Metro line

The second case study aims to explore the role of matrices in the tool developed. Recently, there have been plans for a new metro line connecting Gondomar's São Cosme area to the main Porto metro system, as part of broader expansion efforts. The Porto metro will see the addition of 37 kilometers of new lines across Gondomar, Maia, Matosinhos, Porto, and Trofa, with completion expected by 2030. This project includes four new lines and is funded by 7.4 million euros from the Environmental Fund, supporting various preliminary and environmental impact studies.

In this case study, new matrices were developed with assumptions of what could be the trip and wait times perceived by citizens based on the information available and the conditions regarding the other metro lines. The assumed matrix for the trip times expected is available in Table A.11, and the wait times are available in Table A.12. The goal was to predict the response of citizens to these changes and compare them with the case of no changes to the railway system in the year 2030.

In Table 5.9, it is possible to observe that there is a change in the predicted mobility. Even though the 1.78% difference seems low, it is important to note that metro ridership is low to begin with. This change amounts to 4204 added railway trips. The changes in railway occupancy rates are projected to go from 9.5% to 14%, accounting for the added capacity. This information could mean that the predicted response from citizens surpasses the offer available by bringing new customers to the overall Porto metro lines. In Table 5.10, the results per income group are presented. It is clear that the group that presents the most change is the non-active portion of the population, presenting an extremely significant change in the modal split, especially considering the lack of response to the railway policy. Low-income citizens also present a change in mobility behaviors, though not as significant, still relevant given the small share in railway usage. It is still a 58% growth of trips with the implementation of the new line.

Matrices serve an important role in defining a simplified notion of space in the system. While the previous study aimed to explore the system dynamics implementation of policy, meaning an aggregate change then changes each attribute of the system equally, this case study aims to exemplify how changes to the matrices in target OD pairs can also represent an implementation of policy that could be further explored. These are relevant to use when evaluating cases such as the railway expansion to just one area, as shown in the example presented here.

Table 5.9: Comparison of modal splits and daily trips for the year 2030 between current scenario and new Gondomar line.

Year	Car		Bus		Railway		Walk	
	%	Trips per day	Modal split (%)	Trips per day	Modal split (%)	Trips per day	Modal split (%)	Trips per day
2030 (Current)	59.85	140,570	14.75	34,636	3.85	9,034	21.55	50,622
2030 (New Line)	59.65	140,276	14.49	34,088	5.63	13,238	20.23	47,577
Difference	-0.20	-294	-0.26	-548	+1.78	+4,204	-1.32	-3,045

Table 5.10: Comparison of modal splits across different income groups for the year 2030 between current Metro do Porto lines and the new Gondomar line.

Year	Not Active (%)				Low Income (%)				Medium Income (%)				High Income (%)			
	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk	Car	Bus	Rail	Walk
2030 (Current)	0.00	27.62	8.79	63.59	83.79	13.71	2.51	0.00	91.32	7.53	1.15	0.00	98.40	1.53	0.06	0.00
2030 (New Line)	0.00	27.00	13.19	59.81	82.68	13.51	3.81	0.00	91.10	7.48	1.42	0.00	98.29	1.64	0.08	0.00
Difference	0.00	-0.62	4.40	-3.78	-1.11	-0.20	1.30	0.00	-0.22	-0.05	0.27	0.00	-0.11	0.11	0.02	0.00

Chapter 6

Conclusions

To conclude, in this section, the main contributions of the dissertation will be explored, and future directions to tackle limitations or further develop the model will be presented.

6.1 Main Contributions

The model is designed to explore the synergies between these two approaches in representing urban mobility, offering a comprehensive framework for decision-making in cities. To ensure clarity, this section is divided into three subsections: Scientific Contribution, Applicational Contribution, and Technological Contribution.

6.1.1 Scientific Contribution

In the Literature Review, it was concluded that while System Dynamics models have been proven useful throughout the years in the evaluation of urban mobility policies, the approach has clear limitations due to its nature, the most relevant ones to this dissertation being:

- Incapability to represent spatial Dynamics. (Melkonyan et al., 2020)
- Incapability to include heterogeneous elements. (Łatuszyńska, 2020), (Nguyen et al., 2024), (Mashaly and Fernald, 2020)

These demonstrate clear flaws when representing the response of citizens to infrastructure changes. This is validated when observing the often simplified modal choice described in the models explored. This led to the exploration of Hybrid Approaches between System Dynamics and Agent-Based approaches. To the best of our knowledge, there were no approaches that combined these to represent urban mobility. This work examines the strengths and weaknesses of both System Dynamics and Agent-Based approaches, particularly in the context of urban mobility. Through this exploration, it becomes clear that while System Dynamics provides valuable insights into aggregate behavior and long-term trends, Agent-Based modeling allows for the detailed simulation of individual behaviors and interactions within a population.

In response to the gaps identified, this dissertation presents the development of a Hybrid Model that consists of a System Dynamics Model combined with an Agent-Based modal choice. It has used a detailed framework to provide the reasoning behind the decisions made in the conceptual modeling of the system. While further calibration and more data for the validation are necessary, its main goal was to explore how these two approaches could cooperate to create an integrated system. Going back to the research questions:

- How can System Dynamics and Agent-Based modeling interact in a hybrid approach to represent mobility?

The model developed maintains the structure of the System Dynamics principles, namely being based on feedback loops with aggregate values defining the city characteristics while employing the Agent-based approach where heterogeneous behavior is appropriate. The approach consists of disaggregating and creating a population of agents based on the conditions described, simulating a typical day of commuting, and aggregating the results back to get the final components that feed the predicted indicators. It can be used in the typical System Dynamics use cases, meaning long-term simulations of 20-50 years. While the proposed hybrid model takes longer than general System Dynamics models to simulate, it is still reasonable, taking 8 minutes on average. The exact calibration of the model still needs to be further explored.

- Does the approach improve the traditional evaluation of policy of System Dynamics?

While the quality of the results needs to be further researched with the accurate response of the model to policies, it is advantageous to have a more complex modal choice available for the decision-maker. By disaggregating and seeing the effects of the change in the environment for each individual, there is information on how each group reacted to these policy changes. While it has not been thoroughly explored, the approach allows us to see what areas are more in need of transportation improvements, which are more receptive to change, and the individual predicted effects. Therefore, there are clear advantages to the disaggregation in modal choice to observe the policy response.

6.1.2 Application Contribution

In the context that this dissertation results from a partnership between FEUP, ARMIS, and ITA, the focus is on creating a model that is not only academically robust but also highly relevant and useful for policymakers. To achieve this, the output of the model was based on a set of indicators seen as relevant according to European Commission standards.

This dissertation contributes with case studies that represent relevant scenarios in Gondomar, a city that is exploring the use of tools to develop strategies to tackle the urban mobility needs of its citizens. These case studies serve as practical examples of how the model can be applied in real-life scenarios. By focusing on Gondomar, the research demonstrates the model's utility, providing insights into how it can be used to develop strategies that meet the mobility challenges of its population.

While it is considered that some relationships between variables need to be further developed and validated to provide more accurate results, another iteration of the model could be used in real-life scenarios for different cities, provided they fulfill the data requirements.

6.1.3 Technological Contribution

This work lays the groundwork for developing more specialized and scalable tools, making it a valuable resource for policymakers and researchers looking to address specific mobility challenges in various urban environments. Each subsystem can be replaced or enhanced and be included in the main model. Key directions for further improvement are outlined below, highlighting the potential for further development and enhancement of the tool.

6.2 Future work

While the dissertation development has achieved its main goals, there are several dimensions that could be further developed and explored. In this subsection, the possible improvements for each implementation chapter will be envisaged.

The System Dynamics module was made based on assumptions of relationships between variables. It was both due to a lack of access to data at times and an attempt to simplify the process to focus on the general view of the interaction of the approaches. A main improvement point would be to validate each relationship based on correlation analysis. It would also be relevant to expand the current system to have a view of different dimensions prioritized by European principles, such as energy efficiency, access to public transport, fatalities associated with road accidents, etc. The possible indicators explored in Table 3.3 could indicate further expansion of the model.

In the case of the modal choice implemented through agents, while multiple approaches were explored and ultimately, it was considered that there was not enough data available on the case being studied to properly develop a Logit model, it would be relevant to further explore this approach given disaggregated high-quality data. It is also of interest to explore more intelligent agents through Reinforcement Learning, for example. To get information on congestion, currently each agent only has access to the previous iteration's results. While it is enough to guarantee stable results in little time due to the simplicity of the environment represented, it would be relevant to employ more complex agents through Reinforcement Learning. Other aspects could be employed in what defines an agent, such as age group, priorities, etc. To be more precise, on the data made available by INE regarding the 2018 study on mobility in Lisbon and Porto ([Instituto Nacional de Estatística, I. P., 2018](#)) there is information based on surveys on the priorities of the population when it comes to transportation conditions. This can be used to develop more complex agents that are accurate to the population's behaviors in the target place. In general, the modal choice presented is rather simple, there is a lot of room for improvement, taking into account the already existing models in the literature.

For the general model that integrates both approaches, a clear flaw is that a new population of agents is created for each year based on aggregate values, meaning that the composition of the

population can be different in each iteration due to the nature of the approach. This can insert a variation in the response that is not always accurate. To attenuate this problem, there could be more information on the population composition of each area defined through matrices enriched with more accurate and representative information so there is a more complete and authentic view of the exact distribution of the population and the intrinsic characteristics of its inhabitants. In general, the information based on the matrices for each Origin Destination pair could be explored, possibly creating three levels of aggregation: the overall city, the conditions for transportation and population for each OD pair, and the disaggregate population created based on the previous. The policies could be employed at either the city level or the OD pair defined to have access to different information and policies' impact assessment.

In summary, while the current model lays strong foundations for urban mobility planning, implementing these improvements could significantly enhance its reliability and effectiveness. The proposed advancements would provide policymakers with a more accurate and nuanced tool for evaluating and improving urban transportation systems, ultimately contributing to more sustainable, efficient, and inclusive urban environments.

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Appendix A

Appendices

A.1 Supporting Graphs of System Dynamics module

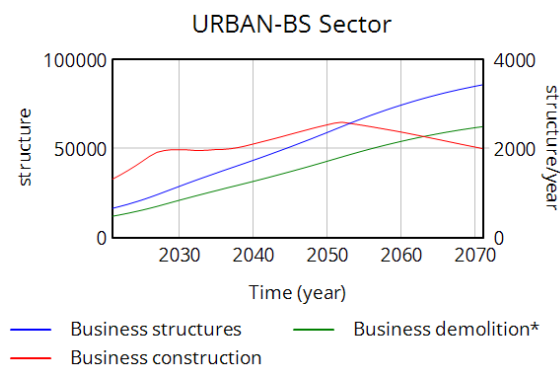


Figure A.1: Projection of the main variables of the Business sector of the Urban model for the city Gondomar.

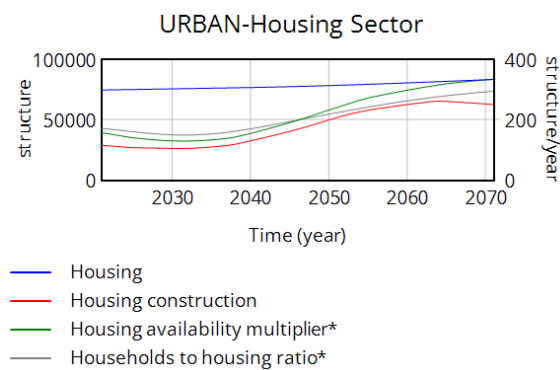


Figure A.2: projection of the main variables of the Housing sector of the Urban model for the city Gondomar.

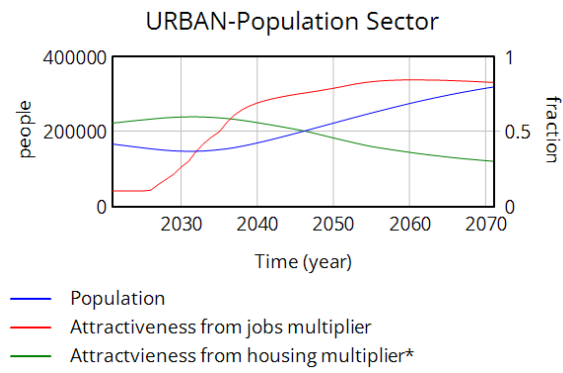


Figure A.3: Projection of the main variables of the Population sector of the Urban model for the city Gondomar.

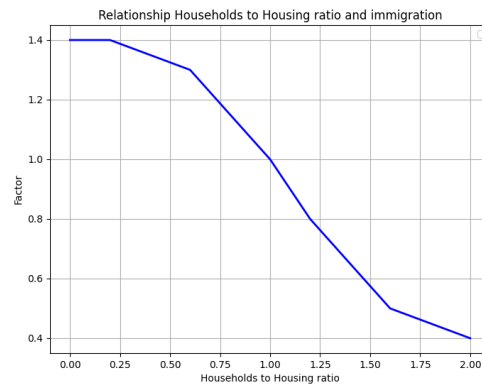


Figure A.5: Relationship used between houses available and immigration (AHM in the model).

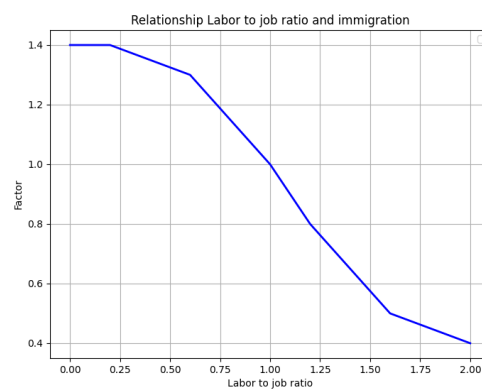


Figure A.6: Relationship used between jobs available and immigration (AJM in the model).

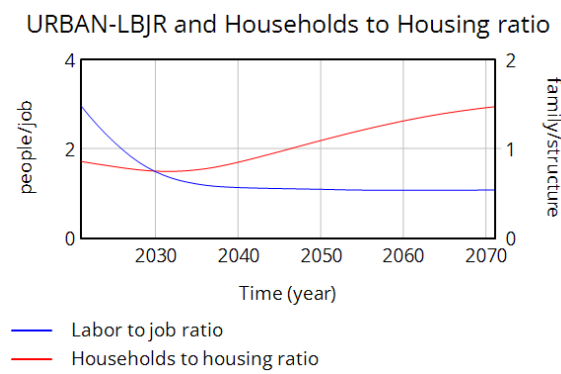


Figure A.4: Projection of the ratios that move the pressures of the city of the Urban model for the city Gondomar.

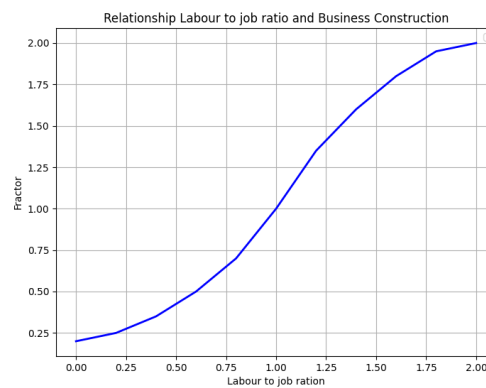


Figure A.7: Relationship used between jobs available and business construction (BLFM in the model).

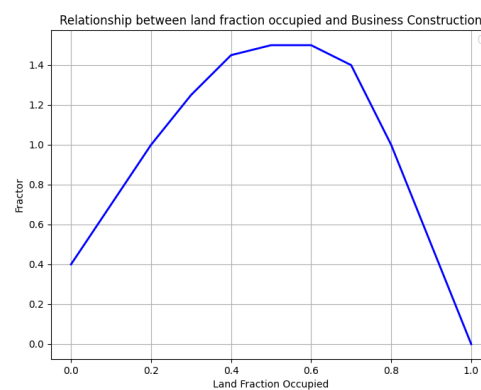


Figure A.8: Relationship used between land available and business construction (BLM in the model).

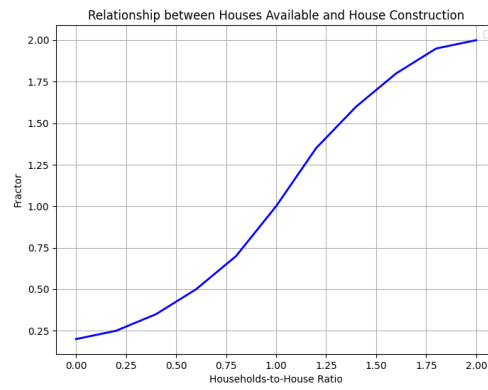


Figure A.9: Relationship used between houses available and house construction (HAM in the model).

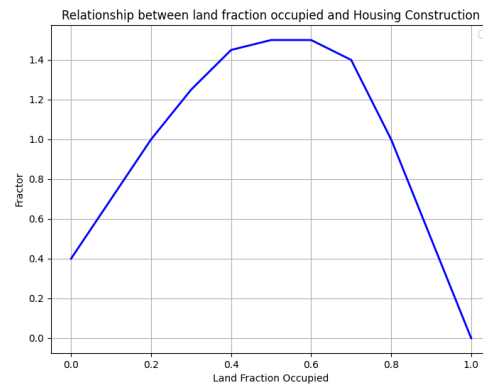


Figure A.10: Relationship used between land available and house construction (HAM in the model).

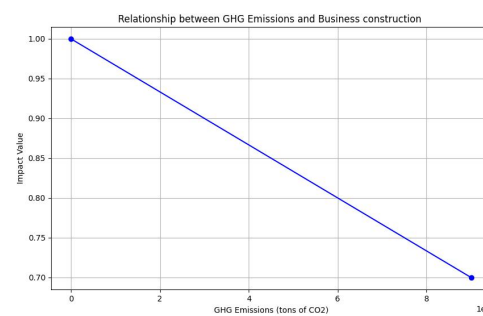


Figure A.11: Relationship used between yearly emissions impact on Business construction (EHE in the model).

A.2 Data used in the model

Table A.1: Data from 2011 used in the model

Name	Units	Value	Source
BCN (business construction)	fraction of the previous year	0.02565	INE
BDN (business demolition)	percentage of the previous year	0.02758	INE
Current value of active companies	company	14502	PorData
Available construction area	m ²	22814900	Câmara de Gondomar
Area per housing unit	m ²	80 to 99 m ²	PorData
HCN Annual housing construction	proportion of existing housing units/year	0.001076	PorData
Cost of car choice per km	euro per km	0.268	PorData
Average walking speed	km/h	4.54	Medical News Today
Number of daily trips	number	266 300	INE
Jobs per Company	jobs/company	2.3	PorData
Active population	percentage	69.6	PorData
Number of people per household	people	2.7	PorData
Population	people	168 363	INE

Name	Units	Value	Source
Births per year	fraction of the population	0.0083	INE
Deaths per year	fraction of the population	0.00732	INE
Immigration per year	fraction of the population	0.0283	PorData
Emigration per year	fraction of the population	0.0215	PorData
Monthly income 2° decil	euro	566	Ministério do Trabalho, Solidariedade e Segurança Social
Monthly income 5° decil	euro	744	Ministério do Trabalho, Solidariedade e Segurança Social
Monthly income 10° decil	euro	3237	Ministério do Trabalho, Solidariedade e Segurança Social
CO2 Emissions Diesel car	g co2/km	140	Example vehicle
CO2 Emissions Petrol car	g co2/km	120	Example vehicle
CO2 Emissions Electric car	g co2/km	42.828	Example vehicle Emissions of electricity
CO2 Emissions Natural Gas Bus	g co2/km	932	Emissions source
CO2 Emissions Electric Bus	g co2/km	348.3	Example vehicle Electricity emissions
CO2 Emissions Diesel Bus	g co2/km	871	Example Vehicle

Name	Units	Value	Source
CO2 Emissions Railway	g co2/km	645	Example Vehicle Electricity emissions
Diesel car proportion	percentage	69%	Direção-Geral de Energia e Geologia (DGEG)
Ticket Cost	euro	0.5575	CNN Portugal
Green Area	m2	59937500	Câmara de Gondomar
Body of Water	m2	1914895	Câmara de Gondomar
Number of Bus Lines	bus lines	94	CNN Portugal
Average trips per Bus Line	trip/bus line	18,489	Câmara de Gondomar
Bus capacity	people/trip	80	STCP
Average Walking Speed	km/h	4.54	Medical News
Number of Rail- way Lines	railway lines	4	CPMetro do Porto
Average trips per railway Line	trip/railway line	75	Metro do Porto
Railway capacity	people/trip	252	Metro do Porto
Average Walking Speed	km/h	4.54	Source
Number of Daily Trips	trips/day	266300	INE

Table A.2: Data used to validate the model

Name	Units	Value	Source
Car split	percentage	65.2%	PorData
Public Transport split	percentage	22.7%	PorData

Name	Units	Value	Source
Walking split	percentage	11.1%	PorData
Income 20	euro	752	Ministério do Trabalho, Solidariedade e Segurança Social
Income 50	euro	919	Ministério do Trabalho, Solidariedade e Segurança Social
Income 90	euro	3526	Ministério do Trabalho, Solidariedade e Segurança Social
Median Income	euro	962	Ministério do Trabalho, Solidariedade e Segurança Social
Population	people	166900	Gabinete de Estratégia e Estudos
Business Structures	structures	16118	Gabinete de Estratégia e Estudos
Housing	houses	74537	Gabinete de Estratégia e Estudos
Bus occupancy rate	fraction	0.101	STCP
Railway occupancy rate	fraction	0.129	Metro do Porto
Motorization rate	vehicles per 1,000 inhabitants	487.11	European Automobile Manufacturers Association)
Percentage of Electric Cars in the fleet	percentage	2%	EV

Table A.3: Data used in the case study

Name	Units	Value	Source
Income 20	euro	752	Ministério do Trabalho, Solidariedade e Segurança Social
Income 50	euro	919	Ministério do Trabalho, Solidariedade e Segurança Social
Income 90	euro	3526	Ministério do Trabalho, Solidariedade e Segurança Social

Name	Units	Value	Source
Median Income	euro	962	Ministério do Trabalho, Solidariedade e Segurança Social
Population	people	166900	Gabinete de Estratégia e Estudos
Business Structures	structures	16118	Gabinete de Estratégia e Estudos
Housing	houses	74537	Gabinete de Estratégia e Estudos
BDN (business construction)	fraction of the previous year	0.0258	INE
BDN (business demolition)	fraction of the previous year	0.00831	INE
Area per house	m2	80	PorData
House Construction	fraction of the previous year	0.001462	PorData
House Demolition	fraction of the previous year	0	PorData
Employees per business	employees	2.3	PorData
Active population	percentage	66,2	PorData
Births	fraction of the previous year	0.007345	INE
Deaths	fraction of the previous year	0.007345	INE
Immigration	fraction of the previous year	0.0671	PorData
Emigration	fraction of the previous year	0.05696	PorData
Average number of people per household	people	2.6	PorData
Diesel proportion of the fleet	fraction	0.7789	Direção-Geral de Energia e Geologia (DGEG)

Name	Units	Value	Source
Petrol proportion of the fleet	fraction	0.29	Direção-Geral de Energia e Geologia (DGEG)
Electric Cars proportion of the fleet	fraction	0.02	EV
Diesel proportion of the bus fleet	fraction	0.18	STCP
Natural Gas proportion of the fleet	fraction	0.77	STCP
Electric Cars proportion of the fleet	fraction	0.05	STCP
Green area	m2	59937500	Câmara de Gondomar
Water area	m2	1914895	Câmara de Gondomar
Number of Bus Lines	bus lines	94	CNN Portugal
Average trips per Bus Line	trip/bus line	18,489	Câmara de Gondomar
Bus capacity	people/trip	80	STCP
Average Walking Speed	km/h	4.54	Medical News
Number of Railway Lines	railway lines	4	CPMetro do Porto
Average trips per railway Line	trip/railway line	75	Metro do Porto
Railway capacity	people/trip	252	Metro do Porto
Public Transport ticket cost	euro/trip with monthly pass	0.67	Metro do Porto
Number of Daily Trips	trips/day	266300	INE
Average lenght of car trip	km	12.8	INE
Average lenght of bus trip	km	16.3	INE

Name	Units	Value	Source
Relationship between population and trips per day	factor	1.607	INE

A.3 Matrices created to support the model

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	0.0045	0.0004	0.0158	0.0116	0.0024	0.0151	0.0017	0.0022	0.0024	0.0084	0.0027	0.0023
Lomba	0.0004	0.00003	0.0012	0.0009	0.0002	0.0012	0.0001	0.0002	0.0002	0.0007	0.0002	0.0002
Rio Tinto	0.0158	0.0012	0.0559	0.0409	0.0084	0.0535	0.0058	0.0076	0.0084	0.0296	0.0096	0.0080
Fânzeres e São Pedro da Cova	0.0116	0.0009	0.0409	0.0299	0.0061	0.0391	0.0043	0.0056	0.0062	0.0217	0.0070	0.0058
Foz do Sousa e Covelo	0.0024	0.0002	0.0084	0.0061	0.0012	0.0080	0.0009	0.0011	0.0013	0.0044	0.0014	0.0012
São Cosme, Valbom e Jovim	0.0151	0.0012	0.0535	0.0391	0.0080	0.0511	0.0056	0.0073	0.0081	0.0283	0.0091	0.0076
Melres e Medas	0.0017	0.0001	0.0058	0.0043	0.0009	0.0056	0.0006	0.0008	0.0009	0.0031	0.0010	0.0008
Maia	0.0022	0.0002	0.0076	0.0056	0.0011	0.0073	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000
Matosinhos	0.0024	0.0002	0.0084	0.0062	0.0013	0.0081	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000
Porto	0.0084	0.0007	0.0296	0.0217	0.0044	0.0283	0.0031	0.0000	0.0000	0.0000	0.0000	0.0000
Valongo	0.0027	0.0002	0.0096	0.0070	0.0014	0.0091	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
Gaia	0.0023	0.0002	0.0080	0.0058	0.0012	0.0076	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000

Table A.4: Origin-Destination Matrix for Travel Patterns

Time	Distribution
12 AM	0.01
1 AM	0.0
2 AM	0.0
3 AM	0.0
4 AM	0.0
5 AM	0.0
6 AM	0.01
7 AM	0.06
8 AM	0.15
9 AM	0.08
10 AM	0.04
11 AM	0.03
12 PM	0.05
1 PM	0.06
2 PM	0.05
3 PM	0.04
4 PM	0.05
5 PM	0.1
6 PM	0.1
7 PM	0.07
8 PM	0.04
9 PM	0.02
10 PM	0.02
11 PM	0.0

Table A.5: Travel distribution of trips

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosinhos	Porto	Valongo	Gaia
Baguim do Monte	1.7	37.5	2.9	2.9	13.1	6.9	27.8	15	15.9	8.1	6.3	11.1
Lomba	36.5	5.5	34.3	32.5	19.6	30.4	25	42	39.5	31.5	37	31.1
Rio Tinto	2.9	35.1	3.3	3.6	12.6	6.4	25.9	11.9	14.8	6.6	8.8	21.3
Fânzeres e São Pedro da Cova	3.3	33.4	3.5	2.1	10.4	4.8	23.6	13.9	16.1	8.1	7.6	12.7
Foz do Sousa e Covelo	12.8	24.8	12.6	10	8.6	7.3	14.1	24.1	23	11.6	16	15.6
São Cosme, Valbom e Jovim	6.9	30.9	6.7	3.6	7.2	4	20	18.8	17.7	7.6	11.5	10.9
Melres e Medas	28	25	26.1	21.4	13.8	18.9	7.4	39.4	38.3	28.2	28	31.5
Maia	15	43.3	12.9	16.3	24.2	19.6	39.6	1	1	1	1	1
Matosinhos	16.5	39.5	14.4	17.8	23.1	18.5	38.4	1	1	1	1	1
Porto	9	31.8	6.2	9.5	11.9	6.6	28.1	1	1	1	1	1
Valongo	5.7	37.3	8.2	7.4	15	11.1	27.5	1	1	1	1	1
Gaia	12.1	33	21.6	13.3	16.8	11.6	31.3	1	1	1	1	1

Table A.6: Road Distances (in KM) between Target Locations

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Lomba	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Rio Tinto	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Fânzeres e São Pedro da Cova	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Foz do Sousa e Covelo	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
São Cosme, Valbom e Jovim	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Melres e Medas	400	400	400	400	400	400	400	2000	2000	2000	2000	2000
Maia	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Matosi- nhos	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Porto	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Valongo	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Gaia	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Table A.7: Road Capacities (in vehicles per hour) between Target Locations

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	1	45	22.5	22.5	45	22.5	52.5	47.5	27.5	10	9	16.5
Lomba	45	1	52.5	52.5	30	30	52.5	55	55	37.5	40	40
Rio Tinto	22.5	52.5	1	22.5	45	10	21	40	27.5	7.5	8	36
Fânzeres e São Pedro da Cova	22.5	52.5	22.5	1	40	20	42.5	50	25	20	35	46
Foz do Sousa e Covelo	45	30	45	40	1	35	15	13.5	22.5	2.5	82	62.5
São Cosme, Valbom e Jovim	22.5	30	10	20	35	1	15	14.5	22.5	2.5	70	62.5
Melres e Medas	52.5	52.5	21	42.5	15	15	1	20	22	5	57.5	13.5
Maia	47.5	55	40	50	13.5	14.5	20	inf	inf	inf	inf	inf
Matosi- nhos	27.5	55	27.5	25	22.5	22.5	22	inf	inf	inf	inf	inf
Porto	10	37.5	7.5	20	2.5	2.5	5	inf	inf	inf	inf	inf
Valongo	9	40	8	35	82	70	57.5	inf	inf	inf	inf	inf
Gaia	16.5	40	36	46	62.5	62.5	13.5	inf	inf	inf	inf	inf

Table A.8: Bus Wait Times (in minutes) between Target Locations

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	inf	inf	4	7	inf	inf	inf	47	47	15	inf	31
Lomba	inf	4	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Rio Tinto	4	inf	4	6	9	inf	inf	43	43	12	13	27
Fânzeres e São Pedro da Cova	7	inf	9	4	inf	inf	inf	50	51	20	29	35
Foz do Sousa e Covelo	inf	inf	inf	inf	4	inf	inf	inf	inf	inf	inf	inf
São Cosme, Valbom e Jovim	inf	inf	inf	inf	inf	4	inf	inf	inf	inf	inf	inf
Melres e Medas	inf	inf	inf	inf	inf	inf	4	inf	inf	inf	inf	inf
Maia	47	inf	42	51	inf	inf	inf	4	inf	inf	inf	inf
Matosi- nhos	47	inf	42	51	inf	inf	inf	inf	4	inf	inf	inf
Porto	15	inf	11	20	inf	inf	inf	inf	inf	4	inf	inf
Valongo	inf	inf	14	29	inf	inf	inf	inf	inf	inf	4	inf
Gaia	31	inf	25	34	inf	inf	inf	inf	inf	inf	inf	4

Table A.9: Railway Trip Times (in minutes) between Target Locations

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	7.5	inf	7.5	7.5	inf	inf	inf	15	13.5	7.5	inf	10.5
Lomba	inf	7.5	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Rio Tinto	7.5	inf	7.5	7.5	7.5	inf	inf	15	13.5	7.5	15	10.5
Fânzeres e São Pedro da Cova	7.5	inf	7.5	7.5	inf	inf	inf	15	13.5	7.5	22.5	10.5
Foz do Sousa e Covelo	inf	inf	inf	inf	7.5	inf	inf	inf	inf	inf	inf	inf
São Cosme, Valbom e Jovim	inf	inf	inf	inf	inf	7.5	inf	inf	inf	inf	inf	inf
Melres e Medas	inf	inf	inf	inf	inf	inf	7.5	inf	inf	inf	inf	inf
Maia	15	inf	15	15	inf	inf	inf	7.5	inf	inf	inf	inf
Matosi- nhos	13.5	inf	13.5	13.5	inf	inf	inf	inf	7.5	inf	inf	inf
Porto	7.5	inf	7.5	7.5	inf	inf	inf	inf	inf	7.5	inf	inf
Valongo	inf	inf	15	22.5	inf	inf	inf	inf	inf	inf	7.5	inf
Gaia	10.5	inf	10.5	10.5	inf	inf	inf	inf	inf	inf	inf	7.5

Table A.10: Railway Wait Times (in minutes) between Target Locations

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	inf	inf	4	7	inf	30	inf	47	47	15	inf	31
Lomba	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Rio Tinto	4	inf	6	9	inf	27	inf	43	43	12	13	27
Fânzeres e São Pedro da Cova	7	inf	9	inf	inf	35	inf	50	51	20	29	35
Foz do Sousa e Covelo	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
São Cosme, Valbom e Jovim	30	inf	27	35	inf	4	inf	47	53	15	35	30
Melres e Medas	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Maia	47	inf	42	51	inf	47	inf	inf	inf	inf	inf	inf
Matosi- nhos	47	inf	42	51	inf	53	inf	inf	inf	inf	inf	inf
Porto	15	inf	11	20	inf	15	inf	inf	inf	inf	inf	inf
Valongo	inf	inf	14	29	inf	35	inf	inf	inf	inf	inf	inf
Gaia	31	inf	25	34	inf	30	inf	inf	inf	inf	inf	inf

Table A.11: Railway Trip Times (in minutes) between Target Locations assumed with the implementation of the new Gondomar metro line

Origin \Destina- tion	Baguim do Monte	Lomba	Rio Tinto	Fânzeres e São Pedro da Cova	Foz do Sousa e Covelo	São Cosme, Valbom e Jovim	Melres e Medas	Maia	Matosi- nhos	Porto	Valongo	Gaia
Baguim do Monte	inf	inf	7.5	7.5	inf	15	inf	15	13.5	7.5	inf	10.5
Lomba	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Rio Tinto	7.5	inf	7.5	7.5	inf	15	inf	15	13.5	7.5	15	10.5
Fânzeres e São Pedro da Cova	7.5	inf	7.5	7.5	inf	15	inf	15	13.5	7.5	22.5	10.5
Foz do Sousa e Covelo	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
São Cosme, Valbom e Jovim	15	inf	15	15	inf	7.5	inf	15	13.5	7.5	22.5	10.5
Melres e Medas	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
Maia	15	inf	15	15	inf	15	inf	inf	inf	inf	inf	inf
Matosi- nhos	13.5	inf	13.5	13.5	inf	13.5	inf	inf	inf	inf	inf	inf
Porto	7.5	inf	7.5	7.5	inf	7.5	inf	inf	inf	inf	inf	inf
Valongo	inf	inf	15	22.5	inf	22.5	inf	inf	inf	inf	inf	inf
Gaia	10.5	inf	10.5	10.5	inf	10.5	inf	inf	inf	inf	inf	inf

Table A.12: Railway Wait Times (in minutes) between Target Locations assumed with the implementation of the new Gondomar metro line