Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Heuristics and Mixed-Initiative System in a Multiagent System to reduce Bus Bunching considering Exogenous Factors

por

Jesús Ángel Patlán Castillo

en opción al grado de

Doctorado en Ingeniería

con Orientación en Tecnologías de la Información

San Nicolás de los Garza, Nuevo León Diciembre 2024

Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Heuristics and Mixed-Initiative System in a Multiagent System to reduce Bus Bunching considering Exogenous Factors

por

Jesús Ángel Patlán Castillo

en opción al grado de

Doctorado en Ingeniería

con Orientación en Tecnologías de la Información

San Nicolás de los Garza, Nuevo León   Diciembre 2024

UNIVERSIDAD AUTÓNOMA DE NUEVO LEÓN
Facultad de Ingeniería Mecánica y Eléctrica
Posgrado

Los miembros del Comité de Evaluación de Tesis recomendamos que la tesis "Heuristics and mixed-initiative system in a multiagent system to reduce bus bunching considering exogenous factors", realizada por el estudiante Jesús Ángel Patlán Castillo, con número de matrícula 1595261, sea aceptada para su defensa como requisito parcial para obtener el grado de Doctorado en Ingeniería con Orientación en Tecnologías de la Información.

El Comité de Evaluación de Tesis

Dr. Romeo Sánchez Nigenda
Director

Dr. Tomás Eloy Salais Fierro
Revisor

Dra. Sara Elena Garza Villarreal
Revisora

Dra. María Isolde Hedlefs Aguilar
Revisora

Dra. Iris Abril Martínez Salazar
Revisora

Dra. Cristina Maya Padrón
Revisora

Vº. Bº.

Dr. Simón Martínez Martínez
Subdirector de Estudios de Posgrado

Institución	190001
Programa	514622
Acta núm.	364

Ciudad Universitaria, a 23 de junio de 2025.

A mis padres, Miguel Angel Patlán Rodríguez y Yolanda Margarita Castillo Prieto,

quienes están siempre para apoyarme.

Contents

List of Figures

List of Tables

Agradecimientos

Agradezco principalmente a mis padres por haberme enseñado los hábitos del estudio.

Agradezco al Dr. Romeo Sánchez Nigenda por su tiempo y dedicación para guiarme a concluir esta tesis y con mis estudios en el posgrado éxito.

Agradezco a mis revisores: al Dr. Francisco Torres Guerrero, al Dr. Tomás Eloy Salais Fierro, a la Dra. Sara Elena Garza Villarreal y a la Dra. María Isolde Hedlefs Aguilar; por dedicar de su tiempo y rigor para la revisión de la tesis.

Agradezco al cuerpo docente de DITI por su disponibilidad para resolver todo tipo de dudas tanto dentro como fuera del aula. Particularmente, agradezco a la Dra. María Isolde Hedlefs Aguilar, a la Dra. Sara Elena Garza Villarreal, y a la Dra. Leticia Amalia Neira Tovar, con quienes tuve clases que directamente trataron sobre mi trabajo de tesis.

Agradezco a mi compañera la Dra. Citlali Maryuri Olvera Toscano por compartirme datos del medio de transporte ECOVIA del estado de Nuevo Leon, junto con nuestros compañeros que en su momento la apoyaron para la recoleccion de datos, y también por su aporte de su modelo lineal que es utilizado por el sistema multiagente para el uso de la estrategia de retención de autobuses.

Agradezco a mi pareja Monserrath Isabel Martínez Miranda por darme el espacio y la compañía en las distintas etapas de mi estudio, desde la licenciatura hasta la culminación del posgrado.

Espero que la calidad de este trabajo refleje el esfuerzo del estudio que he llevado hasta el momento de mi vida.

Resumen

Jesús Ángel Patlán Castillo.

Candidato para el grado de Doctorado en Ingeniería con Orientación
en Tecnologías de la Información.

Universidad Autónoma de Nuevo León.

Facultad de Ingeniería Mecánica y Eléctrica.

Título del estudio:

Heuristics and Mixed-Initiative System in a Multiagent System to reduce Bus Bunching considering Exogenous Factors

Número de páginas: 71.

Objetivos y método de estudio: El objetivo principal de este trabajo de tesis es diseñar y desarrollar un sistema multi-agente con algoritmos heurísticos y un sistema de iniciativa mixta (BUSIMA) para disminuir el amontonamiento de autobuses (bus bunching) en instancias con eventos exógenos, que simulen escenarios más cercanos a la realidad. Para su análisis, se realizan pruebas ANOVA para determinar el nivel de efectividad de los algoritmos heurísticos y del sistema de iniciativa mixta propuesto sobre distintas muestras y escenarios de una red de transporte público.

Contribuciones y conclusiones: En esta tesis se hacen dos aportaciones principales: la primera contribución se relacióna a la definición de tres factores exógenos diferentes, los cuales han sido evaluados identificando el impacto que estos tienen en el rendimiento de las rutas de transporte público. La segunda contribución es el diseño y desarrollo de algoritmos heurísticos, en un entorno de agentes inteligentes, que permiten a los agentes adaptarse a los factores exógenos del sistema. Nuestra evaluación de los algoritmos heurísticos propuestos permite concluir que estos aumentan el rendimiento de las rutas de transporte público en la presencia de factores exógenos, permitiendo al sistema multi-agente propuesto BUSIMA adaptarse a entornos reales del transporte público.

Firma del asesor: ______________________________

Summary

Jesús Ángel Patlán Castillo.

Candidate to the degree of Doctor on Information Technology

Universidad Autónoma de Nuevo León.

Facultad de Ingeniería Mecánica y Eléctrica.

Thesis:

Heuristics and Mixed-Initiative System in a Multiagent System to reduce Bus Bunching considering Exogenous Factors

Number of pages: 71.

Objectives and study method: The primary objective of this thesis work is to design and develop a multi-agent system with heuristic algorithms and a mixed-initiative system (BUSIMA) to reduce bus bunching in instances with exogenous events, simulating scenarios closer to reality. For analysis, ANOVA tests are conducted to determine the effectiveness level of the heuristic algorithms and the proposed mixed-initiative system on different samples and scenarios of a public transportation network.

Contribution and conclusions: In this thesis, two main contributions are made: the first contribution relates to the definition of three different exogenous factors, which have been evaluated by identifying the impact they have on the performance of public transport routes. The second contribution is the design and development of heuristic algorithms, in an intelligent agent environment, that allow agents to adapt to the exogenous factors of the system. Our evaluation of the proposed heuristic algorithms allows us to conclude that they increase the performance of public transport routes in the presence of exogenous factors, enabling the proposed multi-agent system BUSIMA to adapt to real-world public transport environments.

Adviser signature: ______________________

Chapter 1

Introduction

This chapter will initially define the bus bunching problem, its detrimental impact on bus route performance, and the underlying factors contributing to its occurrence. Subsequently, we will justify the contemporary significance of this issue, followed by a historical overview and existing approaches to address it. Finally, the research questions, general objective, specific objectives, hypothesis, and limitations of this study will be outlined.

1.1 Thesis Structure

Figure 1.1 illustrates the thesis structure. It starts with an introduction that defines the bus bunching problem, justifies its significance, provides a historical overview, and outlines the research objectives. The second chapter, which represents the theoretical framework, will establish the fundamental concepts underpinning this study. Subsequently, the methodology will detail the approach to achieving the stated objectives in Chapter 1. The results from applying this methodology will then be presented, culminating in conclusions that validate whether the initial goals were accomplished.

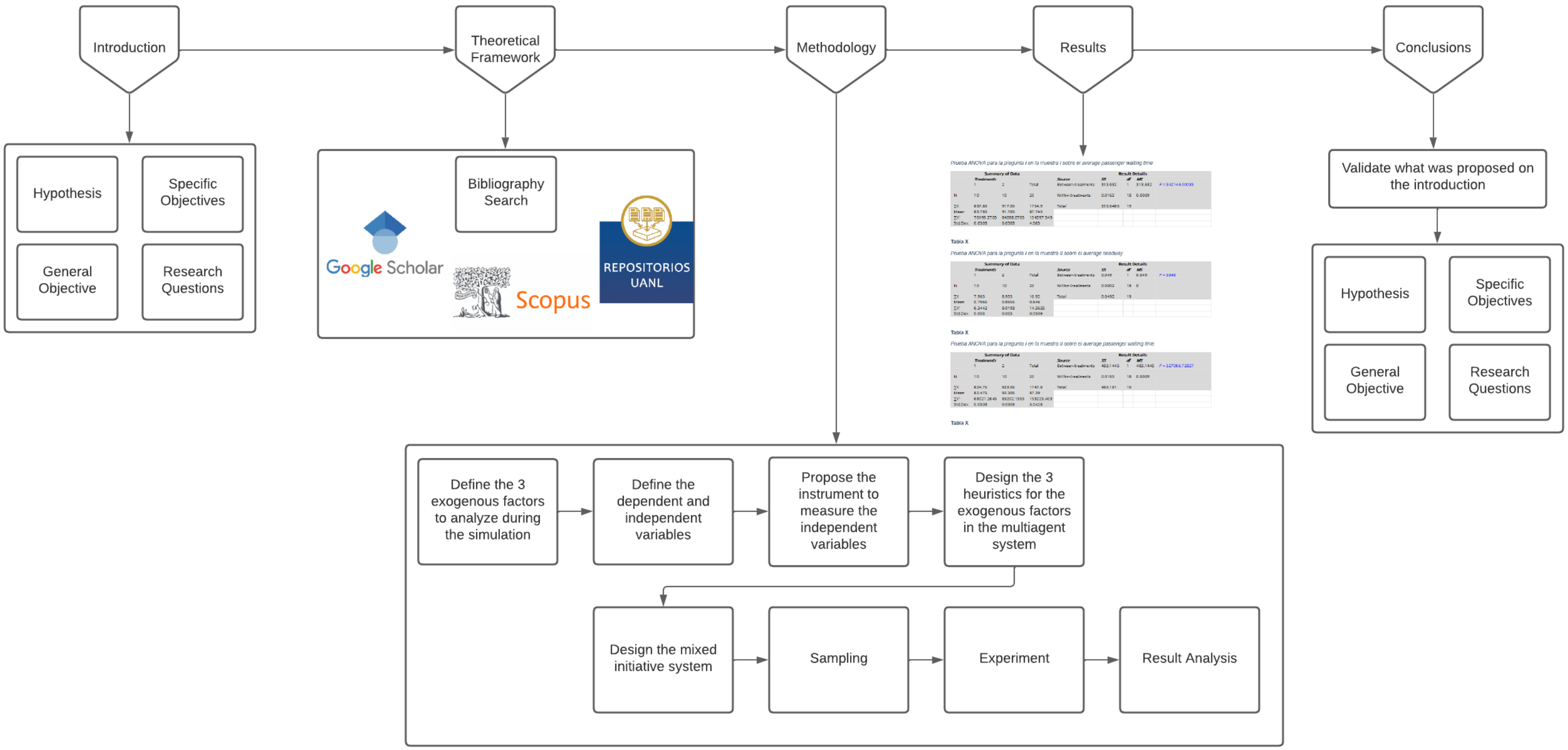

Figure 1.1: Thesis Structure.

1.2 Problem Statement

The bus bunching problem occurs when two or more buses on the same route become too close to each other, disrupting the regular intervals between them. This leads to decreased service efficiency and increased travel times for passengers and buses (Newell and Potts, 1964). Newell and Potts (1964), addressed this problem through a mathematical control model that employed a bus holding strategy. This innovative approach, designed to regulate inter-bus distances, has subsequently been applied to address bus bunching in various contexts (Hickman, 2001; Zhao et al., 2006; Hernández-Landa et al., 2015; Olvera Toscano, 2018; Chen et al., 2021).

Numerous studies have investigated the benefits of mitigating bus bunching on public transport routes. For instance, Cats and Gkioulou (2017) analyzed how the reliability of high-frequency public transport services is influenced by variations in vehicle headway. They found that improving service regularity reduces passenger waiting times while decreasing crowding at stops, enhancing capacity utilization and public transport modes' operational reliability. These findings underscore the positive effects of lowering bus bunching on overall service quality.

Furthermore, understanding the dynamics of exogenous factors that contribute to bus bunching is crucial for addressing the root causes of the problem and improving the efficiency of public bus services. Exogenous factors are external influences not directly controlled by the bus system, such as traffic conditions, weather, network disruptions, or passenger demand variations. For example, a study using a cellular automata simulation of a bus route demonstrated that even a 1-second reduction in passenger boarding and alighting time can significantly affect the system's efficiency (Enayatollahi et al., 2019). This highlights how small external variations in the bus route environment can substantially impact the operational efficiency of buses during service at stops.

Feng et al. (2016) investigates how collaborative and competitive interactions among bus routes sharing a common corridor can influence bus service quality. This collateral effect is crucial to consider when implementing strategies to mitigate bus bunching on routes that share a corridor, as improvements on one route can positively impact the performance of others.

Liang and Ma (2019) demonstrated that crowded buses, especially when there is a significant disparity between the number of passengers aboard and the number boarding or alighting, can exacerbate crowding not only on the same route but also on other vehicles using the same corridor. This underscores the complexity of the bus bunching problem, highlighting its interdependence with other modes of transport sharing the route. One of the reasons Bus Rapid Transit (BRT) systems offer improved service is their use of dedicated lanes, allowing only buses from the same or selected routes to operate, reducing such external dependencies.

One factor beyond the control of both bus drivers and route managers is passenger behavior. However, some approaches can encourage users to act in ways that improve public transport services. For instance, Kaddoura et al. (2015) demonstrated how public transport performance improves when passengers are informed of arrival times and can prepare for boarding. Similarly, Cats and Gkioulou (2017), through a case study in Stockholm, highlighted the importance of user adaptation as passengers respond to bus behavior and service patterns. These "passive" solutions, such as providing real-time information to passengers, can reduce bus bunching without requiring complex strategies for bus drivers. Additionally, offering accurate real-time bus location data significantly enhances user satisfaction, allowing passengers to time their arrival at stops without waiting indefinitely.

Another way to improve public transport service is by collecting data on passenger behavior. A case study in Greater Sydney used data from smart cards to identify times when bus bunching occurs (Du and Dublanche, 2018). The data collected includes passenger frequency of bus use, boarding and alighting times, and stop locations. This information enables a comprehensive analysis of user behavior to inform strategies to balance bus service and minimize bus bunching on routes. Additional studies identified last stop locations, irregular bus dispatch intervals, non-homogeneous fleets, number of intersections, number of routes serving each stop, high demand, and demand variability as some of the most critical factors determining bus bunching (Arriagada et al., 2019; Iliopoulou et al., 2018, 2020b).

Real-time information enables the immediate implementation of optimal strategies to reduce bus bunching, including predictive models that alert bus managers and drivers to potential bunching events or other disruptions. For instance, Sun (2020) used automatic vehicle location (AVL) data from a bus route in Kyoto, Japan, to predict bus bunching with a logistic regression model, achieving better results compared to linear regression and support vector machine methods. Furthermore, Liu et al. (2022b) conducted another study using AVL data, where they developed a deep learning model based on LSTM Kalman filters for travel time prediction. Their model outperformed conventional learning methods in accuracy.

Tsoi and Loo (2022) conducted a study that complements the use of predictive models and artificial intelligence in analyzing bus bunching. They collected data from 25,405 real-time traffic images across 11 bus stops in Hong Kong using AI techniques in analytical visualization. Their analysis revealed that factors like traffic speed, traffic composition, and passenger load are strongly associated with bus bunching. This study highlights the importance of AI in gathering real-time data on bus routes and their environments, enabling more informed decisions on strategies to prevent bus bunching.

Recent studies have leveraged GPS technology to analyze bus behavior, generate predictive models, and plan strategies to mitigate bus bunching. Shan et al. (2023) reached similar conclusions about the factors contributing to bus bunching. By analyzing spatial-temporal data collected from buses' GPS systems, they identified key factors such as traffic congestion, bus capacity, and passenger demand distribution at stops. Their analysis also revealed specific bus bunching patterns, which can be used to develop effective prevention strategies. Similarly, Pan et al. (2023) analyzed the impact of traffic factors on bus bunching and proposed a predictive model to identify and mitigate critical points where bunching occurs. Using GPS data, their model estimates bus speed and passenger waiting times at different sections of the route to determine the causes of bus bunching. Their results highlight that traffic congestion, bus capacity, and variability in passenger demand at stops are the primary factors contributing to bus bunching. An additional work, from Liu et al. (2022a), developed a tiered classification of bus bunching on routes to predict its likelihood, enabling proactive action plans to prevent it. They proposed an XGBoost-based machine learning approach, which effectively classified bus bunching at different levels to support decision-making to improve bus system efficiency.

An important insight into the bus bunching problem is that it does not always negatively impact bus performance. In certain scenarios, bus bunching may be optimal to meet passenger demand. Koppisetti et al. (2018) found that when there is significant variability in bus travel times, reducing bus frequency, despite higher passenger arrival rates at stops, can be optimal for minimizing crowding and wait times. Therefore, bus bunching should not always be viewed as detrimental to route performance. A detailed analysis of its causes is essential to determine whether bus bunching benefits or hinders service efficiency.

Other works have considered the application of simulation models to analyze the behavior of transport networks and propose solutions to the bus bunching problem. Wang (2022) proposed a simulation model based on Boltzmann lattice methods to analyze the impact of traffic flow on avenues. The simulation results showed significant differences in bus travel times under varying traffic density conditions. Bian et al. (2023) introduced a real-time travel speed design approach for multi-line bus routes aimed at minimizing passenger wait times and reducing travel time variance. Their simulation model incorporated interactions between bus lines, traffic congestion, and passenger demand. Results demonstrated that this approach significantly improved bus system performance. Finally, Wang et al. (2024) developed a simulation model to determine passenger arrival times and transfer choices based on the interaction between passenger arrivals at stops and bus positions. Using real-world data, they found that high transfer demand can exacerbate bus bunching in corridors with common-line routes.

1.3 Justification

In Mexico City, one of the most populated cities in the world, the use of bus routes has increased in recent years. Figure 1.2, based on data from the National Institute of Statistics and Geography (INEGI), show the rising percentage of passengers served by buses over the past six years compared to other forms of public transportation.

While these figures indicate that the metro serves more passengers than buses, it doesn't necessarily mean that the metro is always the optimal choice. A recent study found that the metro is more socioeconomically advantageous only when daily demand is double the supply and when there is minimal variation in demand between peak and off-peak hours (Avenali et al., 2020). In most other cases, buses provide a lower social cost while delivering a service quality comparable to that of the metro.

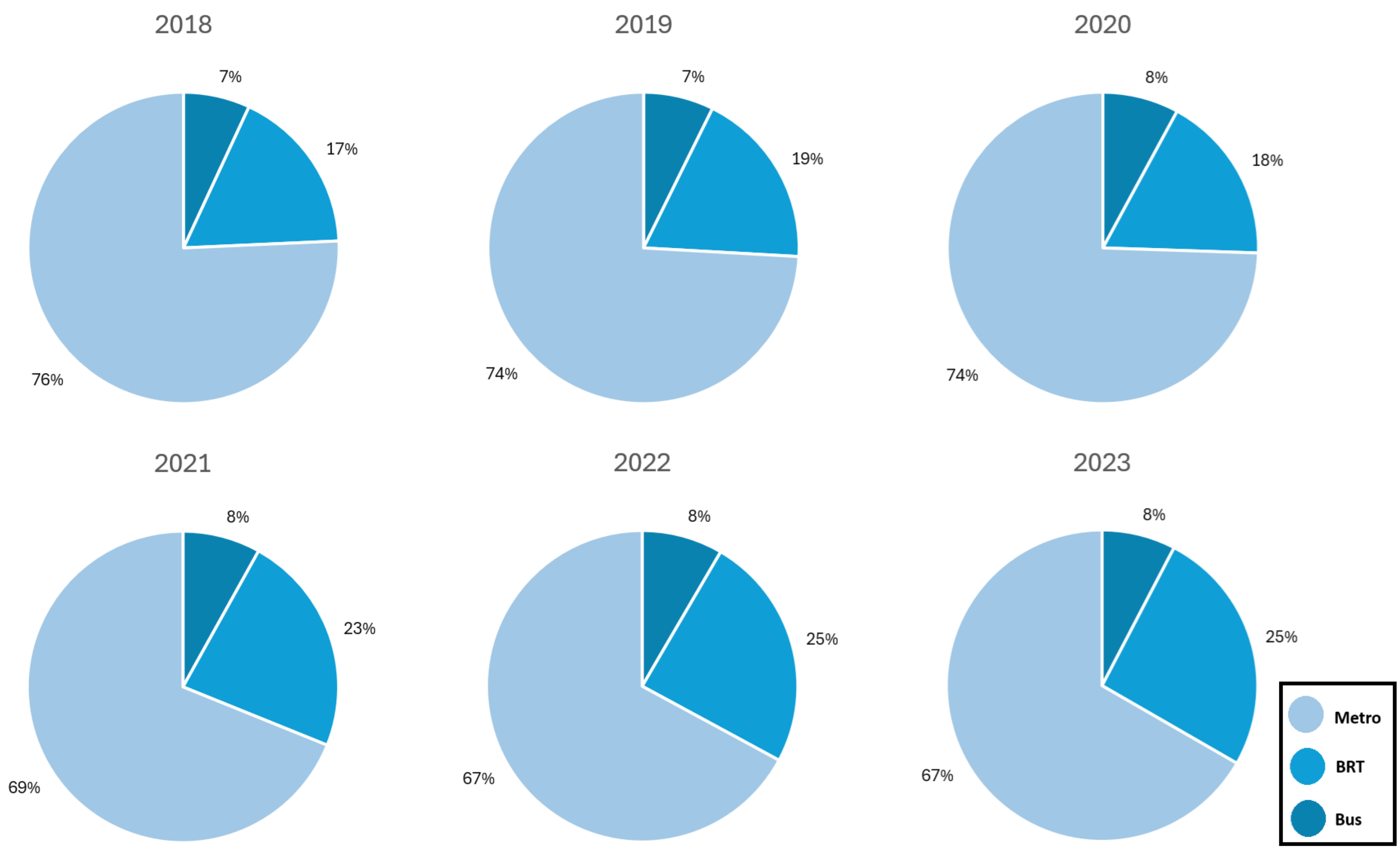

Figure 1.2: Attended passenger percentage by public transport in Mexico City

Figure 1.3 illustrates the growing relevance of the bus bunching problem over the years. In recent years, the use of multi-agent systems to solve the bus bunching problem has steadily increased due to their adaptability, making them suitable for problems involving exogenous events and multiple interacting agents (Torreno et al., 2017; Wang and Sun, 2020; Wang et al., 2021; Wang, 2022). The robustness of multi-agent systems can help maintain consistent distances between buses, thereby reducing bunching and improving route efficiency.

Various strategies, such as bus holding, stop skipping, and speed regulation, have been used in combination to mitigate bus bunching (Patlán Castillo, 2020; Wang and Sun, 2020; Wu et al., 2017; Chen et al., 2016). Implementing these strategies within a multi-agent system, either on individual buses or in coordination across multiple buses on a route, provides greater flexibility. The system can dynamically adjust strategies based on real-time conditions, thereby reducing bus bunching and minimizing passenger wait times.

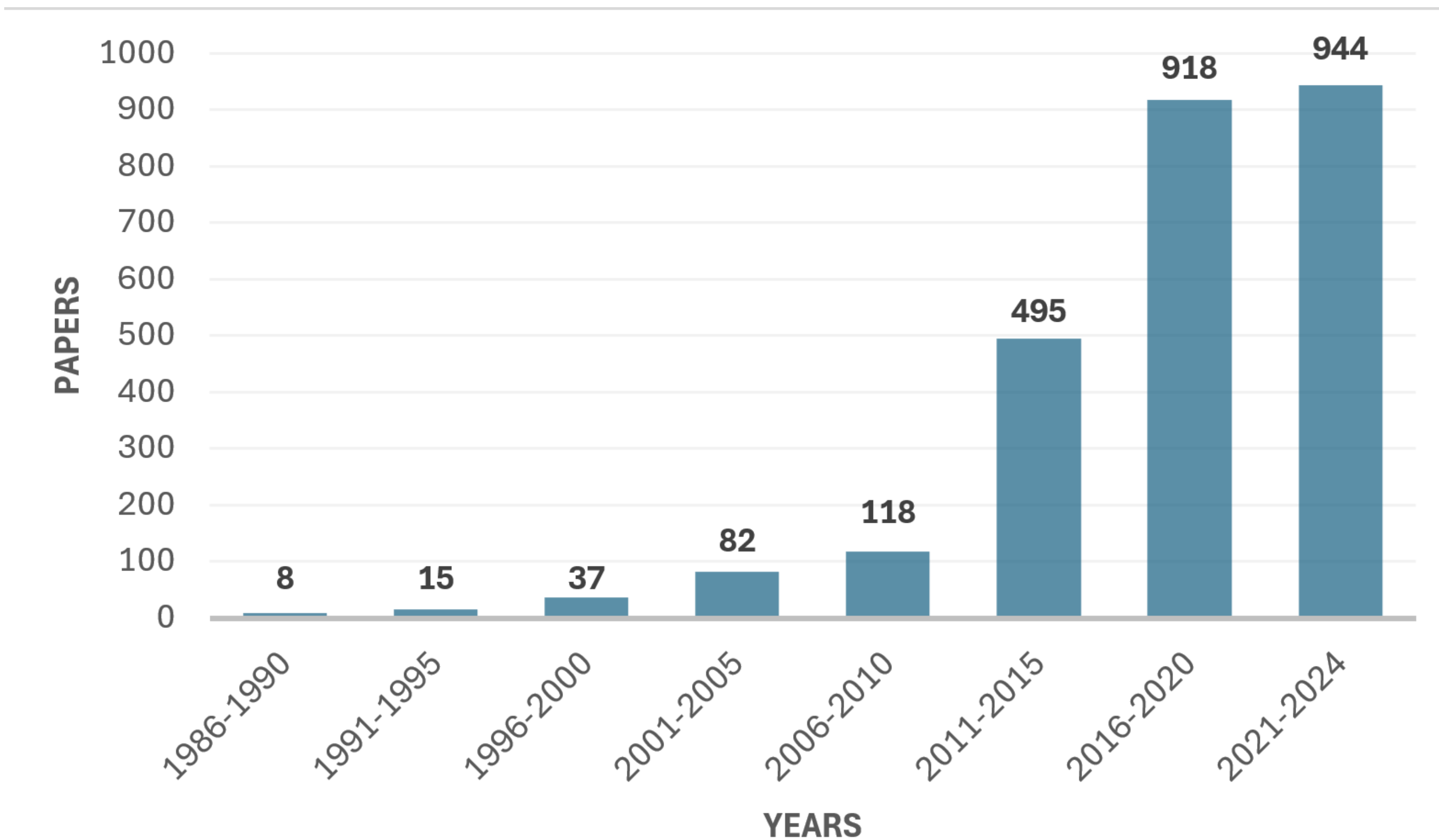

Figure 1.3: Bus bunching related papers

1.4 Background

The public transportation has a great impact on several aspects of the community. The American Public Transportation Association (APTA) performed a research study in 2023 in which it emphasized the following aspects (APTA, 2023):

- Useful: Students and workers take 78% of public transportation journeys to school and work.
- Profitable: Every dollar spent on public transportation is calculated to generate a $5 return, and more than 50,000 new jobs are created for each $1 billion invested.
- Safety: Public transportation is 10 times safer per mile than private transportation.
- Economic: Up to $13,000 per year per vehicle can be saved per family by taking public transportation.

Newell and Potts (1964) first identified the bus bunching problem by analyzing the inherent instability in bus systems. In 1972, they proposed addressing this issue through control models, specifically by incorporating slack time through bus holding to help buses maintain their schedules. Bus holding strategies were used to decrease bus bunching during the 1970's (Barnett, 1974; Ignall and Kolesar, 1974). More recently, control models remain a common approach to mitigate bus bunching, building on the foundation of these early insights (Hickman, 2001; Hernández-Landa et al., 2015; Olvera Toscano, 2018; Chen et al., 2021).

Over time, numerous studies have tackled the bus bunching issue by employing strategies that drivers execute based on mathematical models or computer algorithms. These strategies aim to optimize bus scheduling and spacing, ensuring smoother operation and reduced bunching (Rezazada et al., 2024; Yang et al., 2024). Such strategies are:

- Bus holding, the pioneering strategy to address bus bunching, proposed by Newell and Potts (1964). This strategy requires buses to pause at stops to allow other buses on the route to adjust their spacing. Numerous studies have incorporated mathematical models alongside this strategy to optimize its effectiveness (Adebisi, 1986; Zhao et al., 2016; Wang and Sun, 2020; Moreira-Matias et al., 2016; Hernández-Landa et al., 2015; Liang et al., 2021; He et al., 2020; de Souza and Teixeira Sebastiani, 2021).

- Bus stop-skipping is a commonly used strategy where buses skip stops to maintain proper distances between each other on the route (Suh et al., 2002; Fu et al., 2003; Sun and Hickman, 2005). However, it is not always feasible on certain routes where passenger satisfaction may be compromised if stops are skipped for alighting.

- Deadheading is a variation of the stop-skipping strategy. This approach, driven by mathematical models or algorithms, determines how many upcoming stops each bus should skip to manage spacing (Eberlein et al., 1998). Like regular stop-skipping, it may not be suitable for all routes due to passenger service concerns.

- Bus substitution during working hours addresses bunching by replacing delayed buses with new ones positioned more optimally on the route (Petit et al., 2018, 2019).

- Speed regulation involves adjusting bus speeds to maintain appropriate distances between buses (Bian et al., 2020). Ampountolas and Kring (2020) used a control model based on linear-quadratic Gaussian theory to regulate speeds, applying it to real data from a route in San Francisco, showing marked improvements in bus arrival times.

- Short trip strategy is another method recently applied, where a mid-route stop is set as a turnaround point for buses, allowing for rearrangement and rebalancing of the schedule. Tian (2021) demonstrated its success, achieving up to a 40% improvement in schedule adherence and a 9% reduction in passenger wait times.

Several works have combined the mentioned strategies, under different problem-solving techniques, to address the bus-bunching problem. Comi et al. (2022) introduced a reinforcement learning algorithm that uses real-time data collected through Automated Vehicle Monitoring (AVM) systems installed on buses to mitigate bus bunching. Their algorithm employs bus holding and speed regulation strategies, significantly reducing instances of bus bunching and improving overall route performance.

Wu et al. (2017) employed bus holding and bus substitution strategies to improve bus route efficiency, successfully reducing crowding and enhancing overall service quality. Dual strategies, which combine bus holding and speed regulation, have been considered to reduce bus bunching (Chen et al., 2021) and decrease the wait times of passengers.

Li and Li (2022) applied a predictive model to analyze bus route behavior and traffic light patterns, classifying headways as stacked, stable, or with large gaps. Based on the model's classification, they implemented bus holding, speed regulation, and skip-stop strategies, significantly reducing headway deviation, passenger waiting time, and bus bunching by 77%, 41%, and 87%, respectively.

Vismara et al. (2021) explored bus bunching on cycled routes, finding that increasing the number of stops, while keeping total demand constant, can delay bus bunching. They also demonstrated that intentionally inducing bus bunching at specific peak stops can minimize passenger wait times at those stops, even if it slightly increases waiting times at others. This strategy can improve overall route performance compared to minimizing bus bunching throughout the route (Vismara et al., 2022).

Notice that the strategies just described are actions bus drivers can take during plan execution to reduce bus bunching. However, there are external events that influence the bus bunching phenomena. Such events are called ”exogenous” over which bus routes have no direct control. Exogenous events impacting bus performance have been widely studied. Factors such as the time required for passengers to board and alight (Enayatollahi et al., 2019), the performance of buses on other routes in the same network (Feng et al., 2016), vehicular traffic and congestion (Liang and Ma, 2019), and real-time information available to passengers regarding bus arrivals (Kaddoura et al., 2015) all influence the efficiency of bus services.

The most frequent exogenous factor leading to bus bunching is the inherent randomness of passenger arrival rates at each stop (Welding, 1957). A slight deviation in the spacing of buses, which would otherwise be equidistant, causes one bus to lag behind its front counterpart and move closer to the bus behind it. This misalignment leads to unsynchronized stop arrivals, further exacerbating route imbalance (Gershenson and Pineda, 2009).

Vehicular traffic on the roads where bus routes operate presents random factors that can slow buses during their journey. Traffic congestion and potential automobile accidents can cause buses to become delayed or even go out of service, impacting the entire route’s performance. Recent research also examines how public transportation systems can contribute to overall traffic congestion (Nguyen-Phuoc et al., 2020).

Decisions made by passengers before boarding also contribute to bus bunching. Studies show that choices regarding which bus to board, especially when multiple buses arrive at a stop simultaneously, affect crowding dynamics (Wang et al., 2018; Wang and Sun, 2021). Research by Sun and Schmöcker (2018) indicates that when passengers board the last arriving bus at a stop, the likelihood of bus bunching is reduced, highlighting the influence of passenger decisions on the system’s behavior.

Furthermore, several additional factors contribute to the decline in bus route service quality and exacerbate bus bunching. These include irregular departure schedules, inconsistent frequency, route length, passenger demand, boarding and alighting times, the number of stops on the route (Tirachini et al., 2022), and even buses from different routes traveling on the same roads (Iliopoulou et al., 2020a).

Recent advances have popularized prediction models to combat bus bunching and mitigate the effects of exogenous events on bus routes, yielding favorable results (Yang et al., 2019; Sun, 2020; Gong et al., 2020; Deng et al., 2020; Zhang et al., 2020; Baimbetova et al., 2021; Berrebi et al., 2018). Xin et al. (2021) applied predictive models to regulate bus speed based on traffic light positions, reducing wait times and minimizing bunching. Similarly, Huang et al. (2021) used functional data analysis and Bayesian support vector regression, achieving positive results in bunching reduction.

Andres and Nair (2017) introduced a predictive model coupled with bus-holding strategies to reduce crowding. The holding time was dynamically determined using the predicted and real-time data from the buses. A model developed by Moreira-Matias et al. (2014) utilized a perceptron delta rule to predict bus holding times across multiple routes. The model accurately predicted bus bunching events up to 13 stops ahead, allowing proactive interventions to prevent bunching.

Quek et al. (2021) employed a Monte Carlo-based empirical network model to simulate passenger arrivals using GPS data. They tested bus holding, non-boarding, and centralized pulse strategies on university buses, with the centralized pulse strategy yielding the best results, especially when buses traveled at different speeds.

Gene expression programming and decision trees have also been used to model bus crowding. These models outperformed logistic regression, with schedule deviation identified as the primary factor leading to crowding (Rashidi et al., 2017). Similarly, Chioni et al. (2020) employed geographic weights regression on a route in Athens, finding that bus bunching increases with the number of lanes and bus routes serving a stop. Ma et al. (2021) developed an ensemble decision tree model to predict bus bunching up to 10 stops in advance based on bus position, traffic, and weather data, showing strong predictive accuracy. These prediction models have been equally effective on express bus routes, stabilizing headway progress and improving route efficiency.

Our previous work developed a multi-agent system simulator, BUSIMA, to minimize bus bunching (Patlán Castillo, 2020), utilizing various strategies within a distributed architecture that enables agent coordination. This system is freely available to use to anyone on a GitHub repository. These agents, representing buses, collaboratively adjust their distances from one another on the route. The simulator was tested using data from several instances, including a fast bus route called Ecovía in Monterrey, Mexico (Olvera Toscano, 2018). The results demonstrated a significant reduction in bus bunching across all phases analyzed. BUSIMA was implemented in Java using the JASON library, which supports intelligent agent behavior, environmental interaction, and multi-agent system dynamics (Weiss, 1999).

This thesis plans to incorporate exogenous events into the BUSIMA simulator to assess the robustness of the multi-agent system under real-world, unpredictable conditions. After this integration, the planning and communication algorithms will be fine-tuned to enhance the system's robustness and stability. This will ensure the multi-agent system remains effective in minimizing bus bunching, even in the presence of external disturbances or unforeseen events.

1.5 Research questions

- How much is the difference in performance (bus bunching, passenger waiting time) in a simulation with exogenous events versus a simulation without exogenous events in a multi-agent system framework?
- Does the mixed-initiative system improve the performance of the multi-agent system in the presence of exogenous events?
- Is the multi-agent system robust and adaptive in the presence of exogenous events once heuristics are integrated?
- Are there any combinations of exogenous events that significantly affect the

performance of the multi-agent system?

1.6 General Objective

Design a multi-agent system with heuristics and mixed-initiative support to decrease bus bunching in instances with exogenous events closer to real scenarios.

1.7 Specific Objectives

- Develop three multi-agent system heuristics to minimize bus bunching in the presence of exogenous events.
- Develop a mixed-initiative multi-agent system to consider the human factor for the decision-making process in bus bunching problems.
- Perform a statistical analysis on the simulation performance of a multi-agent system with and without exogenous events to determine how adaptive the system is.
- Perform a design of experiments to determine the best strategy or sets of strategies that minimize bus bunching in the presence of exogenous events.

1.8 Hypothesis

The multi-agent system, enriched with heuristics and a mixed-initiative strategy, will reduce the bus bunching on a bus route in the presence of exogenous events.

Multi-agent systems have been specifically designed to address problems by adapting to dynamic environments through communication, collaboration, and coordination strategies (Torreno et al., 2017). In the context of public transportation domains, multi-agent systems frequently encounter exogenous events that impact the system's performance, which require the application of heuristics to make them adaptable. The heuristics proposed in Chapter 3 are developed with the objective that agents, representing buses in the network, can plan swiftly and effectively in response to the environmental factors that may trigger or exacerbate bus bunching due to various exogenous influences.

1.9 Limitations

The simulation will be conducted on a personal computer, which may impose limitations on computational resources, particularly when simulating complex scenarios that surpass the system's memory and processing capabilities. However, since the experimentation is measured in simulation time units (ticks), the hardware specifications should not affect the accuracy or validity of the results presented in the later chapters. The specifications of the computational system used for these simulations are as follows:

- Operating System: Windows 11
- Processor: Intel i5 11400
- RAM: 16GB
- Storage: 512GB Solid State Disk

Chapter 2

Theoretical Framework

This chapter will present the theoretical foundations and key concepts underlying the research. The discussion will begin with the mathematical modeling of the bus bunching problem, providing a formal framework for analysis. This will be followed by a detailed definition of multi-agent systems, including their characteristics, properties, and how they are used to address complex, dynamic problems. The chapter will also explore how these systems operate in cooperative environments, laying the groundwork for understanding their role in mitigating bus bunching through the strategic interaction of intelligent agents.

2.1 Mathematical Modeling

A bus route is a public transportation service consisting of a fleet of buses and a series of designated stops, with each bus transporting passengers between these stops along a predefined route. The primary goal of a bus route is to meet passenger demand efficiently, ensuring that passengers reach their destination in the shortest possible time. As discussed in the previous chapter, minimizing passenger waiting time is often the central objective in mathematical models addressing the bus bunching problem. However, alternative objective functions can also be considered, such as minimizing headway variability between buses or maximizing the number of passengers picked up.

Given the constraints and complexities outlined earlier, a simulation will be employed to analyze the performance of the multi-agent system in addressing the bus bunching issue. This simulation will allow us to explore and evaluate various strategies and their effectiveness under different conditions. Ross (2022) defines simulation as the imitation of a real-world process over time. Simulations enable the testing of algorithms and models in a controlled environment before their implementation in real-world scenarios, allowing for performance and effectiveness analysis of the proposed approaches. The simulation environment must incorporate as many characteristics of the real system as possible to produce results that apply to real-world conditions.

In addition to capturing realistic dynamics, it's essential to classify correctly the features integrated into the simulation environment. These should be distinguishable as independent variables that directly influence the outcome of the system. A thorough analysis of the factors in the real environment is needed to ensure that only relevant variables are integrated and controlled. This ensures that the effects of the independent variables on the dependent variables can be accurately measured and that no unforeseen extraneous variables obscure the results.

Mathematical models are commonly employed in simulations, as they provide a formal language to represent and analyze the behavior of real-world scenarios (Marion, 2008). By expressing complex phenomena through mathematical equations and relations, these models enable the development of theories to explain and predict the behavior of systems. When combined with simulation, mathematical models offer a way to test and validate theories computationally before applying them in real-world scenarios. Mathematical models enable the use of optimization techniques to solve optimally complex problems. Linear programming provides optimal solutions for models with continuous linear variables, while integer programming is used for models with discrete domain variables. Combining these techniques results in Integer-mixed programming(Andréasson et al., 2020). This mixed-integer programming approach has been applied in several studies to model the bus bunching problem (Hernández-Landa et al., 2015; Olvera Toscano, 2018).

Probabilistic models are also used to simulate specific scenarios on bus routes, such as passenger arrival rates at bus stops. Descriptive statistics helps identify key characteristics of data sets, while inferential statistics enables us to make conclusions about a broader population from a sample of data. Both areas of statistics rely heavily on probability, which allows us to estimate the likelihood of certain outcomes, providing valuable insights into the composition of a population (Mendenhall III et al., 2007). Unlike mathematical models that aim for exact solutions, probabilistic models produce probabilistic distributions, offering a range of possible outcomes rather than a single deterministic result (Alon and Spencer, 2015). For example, the passenger arrival rate at bus stops, in the bus bunching problem, can be simulated with the Poisson probability distribution (Hernández-Landa et al., 2015; Olvera Toscano, 2018):

$$p(r; \mu) = \frac{\mu^r e^{-\mu}}{r!}$$

The variable r is a non-negative integer and the variable μ is a positive integer. The Poisson distribution describes the probability of exactly r events occurring in a given time interval, if the events occur independently at a rate of μ.

A simulation must closely mimic real-world scenarios to ensure the reliability of the results in analyzing the performance of implemented algorithms. However, real-world processes often involve exogenous events that are difficult to manage and can disrupt the efficiency of the algorithm. To address such challenges in the context of bus routes, this research proposes using a multi-agent system combined with a mixed-initiative system, which will be defined later in this chapter, to incorporate human input into the decision-making process of bus drivers. This hybrid approach aims to improve adaptability and decision-making in response to unpredictable events.

2.2 Object Oriented Programming

The multi-agent system and the mixed-initiative system proposed in this research utilize the object-oriented programming paradigm for both data representation and function implementation. The key characteristics of object-oriented programming include the following (Balagurusamy, 2008):

- **Encapsulation**: A grouping of data and methods that act on that data into a single unit, or class, while limiting access to some of the object's components for safety and modularity.
- **Abstraction**: Simplifying complex systems by modeling classes suited to the problem, while hiding implementation details and exposing only the required parts of the code.
- **Inheritance**: Capacity to create new classes from already existing ones, enabling code reuse and creating hierarchical relationships among classes.
- **Polymorphism**: Capacity to treat objects differently depending on their data type or class, enabling the same method to act differently depending on the object on which it is used.

Objects are indeed the fundamental runtime entities in an object-oriented system, representing user-defined data through structured data types (Balagurusamy, 2008). In the multi-agent system of this research, each entity in the bus route environment—such as buses, stops, and passengers—is modeled as an object. These objects have their own attributes (e.g., bus speed, stop location, passenger count) and methods (e.g., boarding, alighting, adjusting speed) that allow them to interact with each other and store relevant information throughout the simulation run. This structure enables efficient data management and interaction in the simulation.

Due to the previously described benefits, such as encapsulation, inheritance, and modularity, object-oriented programming was chosen for the development and implementation of the heuristics and mixed-initiative system integrated into the multi-agent system. This approach enables better organization and flexibility in managing the different entities involved in the simulation, allowing the system to handle complex interactions between buses, passengers, and stops. Additionally, it facilitates the integration of new features and strategies to improve decision-making processes within the system.

2.3 Intelligent Agents

A multi-agent system is composed of several agents working together to solve problems or perform tasks cooperatively. To understand this, we first need to define what an agent is. According to Russell and Norvig (2016), an agent is an entity that perceives its environment via sensors and acts upon it through actuators. Among these, rational agents are those that act in a way that maximizes their expected performance, based on their perceptions of the environment.

Weiss (1999) classifies agents into several categories that lead to the architecture of intelligent agents:

- **Logic-based** agents: These agents make decisions through logical deduction, using a set of predefined rules and logic to determine the appropriate actions.
- **Reactive** agents: These agents operate by mapping situations directly to actions. They respond to stimuli from the environment without involving complex deliberation.
- **Belief-desire-intention (BDI)**: These agents make decisions based on their beliefs about the world, their desires (objectives), and their intentions (plans for achieving those desires).
- **Agents with layered architecture**: These agents divide decision-making across multiple software layers, where each layer operates at a different level of abstraction and reasoning.

An intelligent agent not only acts correctly but performs the best possible actions based on its current environment and situation. Weiss (1999) elaborates on the behavior types that define an intelligent agent:

- **Proactivity**: Intelligent agents exhibit goal-oriented behavior by taking initiative to achieve their objectives. This proactive nature is crucial for problem-solving and fulfilling tasks required by the environment in which they operate.
- **Reactivity**: These agents can perceive changes in their environment and respond promptly to those changes. Reactivity ensures that the system adapts dynamically to unforeseen events or fluctuations in the problem space.
- **Social bonding**: Intelligent agents interact with other agents to achieve their goals, which allows them to share environmental information, improve decision-making, and coordinate actions for mutual objectives.
- **Autonomy**: Agents operate independently, making decisions and taking actions based on their understanding of the environment and the problem they aim to solve. This independence enables them to display unique behaviors suited to their specific needs and circumstances.

These behaviors are key to designing multi-agent systems capable of efficiently handling complex and dynamic problems, such as bus bunching in public transportation.

2.4 Multi-agent systems

A multi-agent system (MAS), on which our solution BusiMA is based, is a collection of multiple intelligent agents that interact and coordinate to solve complex problems that are difficult or impossible for a single agent to tackle (Sycara, 1998; Bordini et al., 2007; Weiss, 1999). These systems are a key area within distributed artificial intelligence (DAI), which focuses on the interactions and coordination between autonomous agents to achieve goals collectively or individually (Bond and Gasser, 2014).

MAS operates in decentralized environments where agents have limited information and control over the system but work together to achieve shared or individual goals (Ferber et al., 2003). The agents in a MAS may have different roles, capabilities, and knowledge about the environment, and their coordination is crucial to ensure success. These systems can be applied in various domains such as transportation, robotics, and network optimization.

Multi-agent systems are characterized as asynchronous systems where data is typically decentralized, meaning that no single agent has complete knowledge of the entire system. Each agent operates based on its own limited perspective and local information (Durfee and Rosenschein, 1994). While this might seem like a computational disadvantage, it allows for more realistic simulations by replicating the way real-world agents work, such as bus drivers, which only have access to real-time data and their immediate surroundings. This decentralized nature encourages flexibility and adaptability, enabling agents to make local decisions while coordinating with others when necessary. The multi-agent system, proposed in this work, follows these properties.

2.5 Multi-agent organization

From a sociological point of view, organizations are defined by their external behavior and structure, which persists regardless of agent participation. However, in distributed artificial intelligence (DAI), MAS focuses on the individual agents' mental states and their contributions to system-wide behavior (Weiss, 1999). An organizational structure in MAS must meet the following requirements (Weigand and Dignum, 2004):

- **Internal autonomy:** The interaction should remain independent of the agent's internal design.

- **Collaborative autonomy:** The organization should allow flexible interactions without predefined constraints.

Agents in a MAS interact through cooperative or non-cooperative behaviors, depending on whether they share a common goal or pursue self-interest (Weiss, 1999; Padgham and Winikoff, 2005). This leads to two organizational approaches:

- **Structural approach:** Focuses on coordination mechanisms for achieving global goals.

- **Institutional approach:** Relies on norms and regulations to govern agent interactions, which dictate acceptable behavior.

An organizational structure is defined as "that which persists when components or individuals enter or leave the organization, that is, the relationships that make the aggregate of elements a whole" (Ferber et al., 2003). This emphasizes the continuity of the organization despite changes in its components. Based on this concept, Horling and Lesser (2004) define a multi-agent organization as a collection of roles, relationships, and authoritative structures governing its behavior. These structures enable the agents to collaborate, coordinate, and achieve collective goals effectively within the multi-agent system. This perspective highlights the importance of roles and interactions in sustaining an organization's functionality, even in dynamic, agent-based environments.

The main aspects that must be represented in any model involving organizational effectiveness or behavior are Weiss (1999); Yokoo et al. (1998):

- **Environment**: Refers to the organization's space. If it is not fully controllable by the organization, then outcomes are not always guaranteed. The environment can include the description of tasks, exogenous events, and resources, characterized by properties such as volatility, scarcity, unpredictability, and complexity.

- **Agents**: These are the acting and reasoning entities in the organization. They possess the partial ability to control elements of the environment and are defined by their capabilities, such as learning, communication, reasoning, and decision-making.

- **Structure**: This encompasses the organization's characteristics, including objectives, roles, relationships, and strategies. It defines the control, coordination, and power relationships, including factors like the structure's size, centralization, and formalization.

Agents, in a multi-agent system, are intelligent and artificial entities that possess the following characteristics:

- Autonomy: This characteristic enables an agent to make independent decisions and perform actions. The decision-making process varies by model, with this work using the Belief-Desire-Intention (BDI) model (explored in the next section).

- Reactivity: It refers to an agent's capacity to respond to environmental changes or events, ensuring responsiveness to dynamic conditions.

- Social Capability: Agents can interact and communicate with other agents, facilitating information sharing to improve decision-making and enable collaborative actions.

- Proactivity: This attribute allows agents to initiate actions and decisions to achieve specific objectives, supporting goal-driven behavior.

2.6 Social Ability in Multi-Agent Systems

As discussed in previous sections, agents in a multi-agent system (MAS) generally lack complete knowledge of the environment in which they operate. The social ability of agents allows them to interact with each other, exchanging information and making decisions based on their individual perspectives and the knowledge they share. Through this interaction, agents can make more informed decisions.

Given their social capabilities, agents in a MAS can negotiate to obtain resources or information necessary for achieving their goals. Negotiation within MAS requires four key elements (Weiss, 1999):

- A defined set of possible outcomes following negotiation or information exchange.
- The agents involved in the negotiation process.
- A protocol that governs how agents seek a common agreement.
- Individual strategies that determine each agent's behavior based on their preferences and available information.

Negotiation outcomes in MAS can be classified into three domains (Rosenschein and Zlotkin, 1994):

- Task-Oriented Domains: Focuses on the division of tasks to be executed, where the agents' preferences are influenced by the costs associated with tasks, and each agent aims to minimize its task-related costs.
- State-Oriented Domains: Involves collaborative decision-making about desirable states. Agents prefer states that align with their own goals. Each agent seeks to reach its preferred states.

- Value-Oriented Domains: Involves deciding jointly on the objectives to pursue. Preferences are based on the number of individual goals each outcome fulfills. Each agent seeks to achieve as many goals as possible.

Agents' social abilities also enable them to engage in argumentation, where arguments serve as "reasons to support or criticize an assertion that is questionable, or open to doubt" (Walton, 2005). The argumentation process involves four steps (Weiss, 1999):

1. Constructing arguments (supporting or opposing statements) from available information.
2. Identifying conflicts among arguments.
3. Assessing the acceptability of various arguments.
4. Formulating justified conclusions.

A MAS can contain diverse types of agents, enabling systems with different agent groups to pursue various objectives. This diversity facilitates the simulation of scenarios where agent groups may have competing or opposing goals. Furthermore, MAS can dynamically adapt and apply heuristics to respond to unexpected environmental changes, and this flexibility has been utilized in addressing issues like bus bunching (Neumann and Nagel, 2010; Kieu et al., 2016; Zhou et al., 2017).

The reactive and social capabilities of agents in a MAS are often modeled using game theory. Abramson (2006) defines game theory as the study of outcomes resulting from strategic interactions among rational agents. Game-theoretic models evaluate agents' decision-making preferences to optimize outcomes.

Problems encountered in MAS are often classified as Distributed Constraint Satisfaction Problems (DCSP). A Constraint Satisfaction Problem (CSP) involves finding a consistent assignment of values across a set of variables. A DCSP extends this concept, distributing the variables and constraints across the intelligent agents in the system (Yokoo et al., 1998).

2.7 Multi-agent system environment

In multi-agent system (MAS) simulations, accurately modeling the environment is fundamental to ensuring that the simulated MAS behaves as expected and that the problem is accurately represented. The environment in a MAS is considered a primary abstraction that sets the conditions for agents to exist, facilitates interaction among agents, and provides access to shared resources (Weyns et al., 2007). Agent environments have several defining characteristics (Russell and Norvig, 2016):

- Observable: An environment is fully observable if an agent, via its sensors, can perceive the complete state of the environment. It is partially observable if an agent perceives only a portion of the environment's state, and it is completely unobservable if the agent cannot access any environmental data, either due to a lack of sensors or environmental constraints. In the context of a bus route, the environment is partially observable because bus agents can perceive their surroundings and communicate with each other and with a checkpoint agent. However, this provides only partial knowledge of the entire bus network.
- Deterministic or stochastic: If the next state of the environment can be predicted based on the current state and the agent's actions, the environment is considered deterministic; otherwise, it is stochastic. In a bus route, due to the existence of random and external events, the environment is stochastic.
- Episodic or sequential: In episodic environments, agents' actions do not influence future outcomes, while in sequential environments, current actions can impact future events. A bus route environment is sequential since the actions of bus agents, such as adjusting speed, can increase or decrease bus bunching, affecting the route's stability and performance.

- Dynamic or Static: A dynamic environment changes state independently of agent actions, while a static environment changes only in response to agents. The bus route environment is dynamic because it is always changing, regardless of the bus agents' decisions.

- Discrete or Continuous: Discrete environments feature time states where actions or perceptions occur at set intervals (ticks). Continuous environments, by contrast, involve continuous perceptions and actions. In a bus route simulation, the environment is continuous because agents are continuously perceiving speed and location to adjust their actions accordingly.

For this research, the BusiMA software will be used to simulate the MAS. BusiMA is a specialized simulator for analyzing MAS performance across different strategies on bus routes (Patlán Castillo, 2020). Custom programming adjustments will be applied to incorporate exogenous events, allowing for a detailed analysis of MAS performance. Further technical details will be outlined in the next chapter.

2.8 Belief-Desire-Intention (BDI) Model

The BusiMA simulation software is based on the Belief-Desire-Intention (BDI) model, a widely used framework for developing autonomous agents in multi-agent systems (MAS) (Bordini et al., 2007). The BDI model is designed to mirror rational decision-making processes, enabling agents to make context-aware choices.

In the BDI model, beliefs represent the agent's knowledge about its environment and other agents, which may vary in accuracy depending on the agent's data-gathering capabilities and its "trust" in the information shared by others. Desires Represent the goals or states the agent seeks to fulfill. While achieving all desires may not be feasible, the agent's actions aim to maximize desire fulfillment. Finally, the intentions are the specific actions the agent commits to based on its beliefs and desires.

Due to potential exogenous events, agents may not always fulfill their intentions, necessitating heuristics to adapt accordingly. Intentions pose challenges that agents must overcome; therefore, agents monitor and may retry actions if an intention fails.

A fundamental part of multi-agent systems is the adaptation of the agents to the environment and the problems they are facing to maintain the robustness and efficiency of the system. For individual agent adaptation, machine learning methods allow agents to adapt to new circumstances present in the environment and to detect and extrapolate patterns (Russell and Norvig, 2016).

In particular, multi-agent learning studies definitions, algorithms, interactions, and reward structures to create adaptive agents that function in an environment where their actions shape them and are shaped by the actions of other agents (Weiss, 1999). Most multi-agent learning algorithms are based on machine learning algorithms, such as supervised learning, unsupervised learning, and reinforcement learning, among others, considering the possibility of using multiple agents in the environment (Weiss, 1999).

The heuristics generated by multi-agent systems stem from the basic concepts of automated planning. Automated planning is the representation of future behavior composed of actions to be executed by one or more agents (Ghallab et al., 2004). Particularly, in multi-agent systems, multi-agent plans are generated, which consider the interaction between agents to execute the generated plan (Russell and Norvig, 2016).

Multi-agent control refers to how agents in a multi-agent system can be provided with information and how they use it to make better decisions for what to do at that moment, while multi-agent planning does not focus only on current choices, but on a succession of decisions, which allow the agent to see further, in such a way that allows it to establish conditions for another agent to achieve some shared accomplishment (Weiss, 1999).

Agent programming is based on the Agent-Oriented Programming (AOP) paradigm that first appeared in an article written by Shoham (1993). The programming language introduced in the article was called AGENT0. Other agent-oriented programming languages popularized in the 1990s were METATEM, Golog, AgentSpeak, and 3APL (Weiss, 1999).

Multi-agent-oriented programming (MAOP) requires several essential features to enable agents to work within a dynamic and interactive environment (Weiss, 1999). For example, agents must be able to react to events and long-term goals, execute action flows based on their circumstances, perform just-in-time planning, handle failed plans, work under rational behavior, communicate and act on messages, and adjust their operational code in real-time to meet the system's evolving demands.

One of the most well-known languages for multi-agent-oriented programming is JASON (Weiss, 1999). JASON is based on the BDI model, which enables the representation of agent behavior, social interactions, and environment simulation. JASON integrates with Java, providing access to many libraries that facilitate robust multi-agent system implementation.

The design phase in MAOP addresses key structural aspects for developing multi-agent systems. The design has to define the agent types, roles, and goals, the communication protocols among agents, the coupling degrees of agents, and the agent functionality.

2.9 Mixed-Initiative Systems

Mixed-initiative systems facilitate collaborative interactions in which each participant (human or automated agent) contributes in ways that are most relevant to the task or context at any given time. Walker and Whittaker (1995) describe an initiative as "taking the lead in the conversation," whereas Smith (1994) defines it as "handling a task".

This shared control fosters flexible problem-solving, with agents (both human and artificial) contributing strategically to optimize task completion and decision-making processes (Allen et al., 1999).

Chanel et al. (2020) examined the effects of mixed-initiative interaction in human-agent collaboration, finding that joint problem-solving enhances adaptability and improves performance in achieving objectives. Their research demonstrated how such interactions allow for timely countermeasures, significantly enhancing system robustness.

In contexts such as bus route management, implementing a mixed-initiative system is essential for a realistic simulation, as bus drivers may make decisions that differ from those recommended by the multi-agent system. This divergence reflects real-world variability and emphasizes the importance of human judgment in operations. For effective implementation, system usability is a priority since operators may lack specialized knowledge in information technology. Guidelines for designing usable mixed-initiative systems thus ensure accessibility and intuitive interaction, accommodating a range of user expertise (Kumarswamy, 2020).

Chapter 3

Methodology

This chapter details the steps taken to carry out the experimentation needed to answer the research questions, achieve the objectives, and evaluate the hypotheses presented in Chapter 1. Figure 3.1 depicts a high-level flow of the research methodology, which considers the definition of the exogenous, variables and collection instruments of the problem, the design of heuristics and the mixed-initiative system, and the experimentation and analysis of the results.

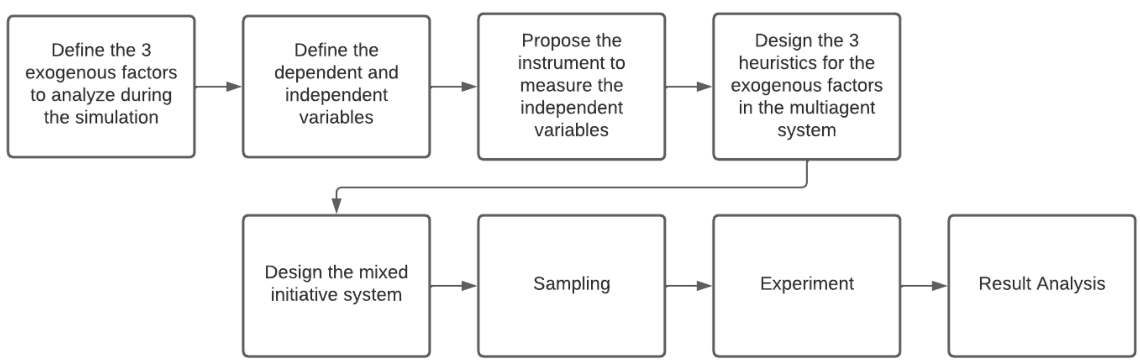

Figure 3.1: High-level methodology process.

3.1 Exogenous Factors

Three exogenous factors were selected to simulate disruptions on the bus route and analyze how agents mitigate these effects: random speed limits, passenger arrival rate variations, and random bus breakdowns.

- Random Speed Limits: Speed limits on routes between stops are randomized, mimicking events like traffic or construction conditions. Parameters include the probability of speed increases or decreases.

- Passenger Arrival Rate Variations: Passenger arrival rates at stops are randomized to reflect variations in demand. Parameters include the likelihood and degree of demand fluctuation.

- Random bus breakdowns: External events to simulate bus breakdowns or accidents. A suspension probability is applied at each time unit, testing the multi-agent system's resilience to bus outages.

3.2 Independent and dependent problem variables

We define a set of dependent and independent variables, which can be parameterized, to assess the effectiveness of the multi-agent system's heuristics against exogenous factors. Independent variables allow customization of the MAS environment and experimentation, while dependent variables allow for answering the research questions outlined in Chapter 1.

Independent Variables consider the following factors: the presence or absence of the exogenous factors described in the previous section, the presence or absence of agent heuristics, the presence or absence of user interaction (i.e., mixed-initiative system), the presence or absence of bus bunching strategies (i.e., bus-holding, skip-stop, deadheading, and speed regulation).

The dependent variables answer the hypothesis and research questions proposed for this work. These variables provide results for the average bus headway deviation and the average passenger waiting time. The first variable is calculated for each time unit of the simulation, tracking the variability in spacing between buses.

The second variable measures how long passengers wait, from arrival at a stop until bus pick-up, in simulation time units.

3.3 Design Instrumentation

Instruments are specified to capture and measure independent variable effects accurately. Positions of buses and distances between each pair of buses are saved and analyzed in real-time. These calculations provide an ongoing record of headway deviation and passenger waiting times across each simulation run.

3.4 Heuristics

Heuristics were created to allow the multi-agent system to respond adaptively to exogenous disruptions, thereby mitigating the effects on bus performance. The agent heuristics take into account several variables like the current position and capacity of each bus, current passenger arrival rate at each stop, speed limits between stops, and positions of the buses on the public transport network. The proposed heuristics are the speed-limiting bus-holding heuristic, dead-heading level heuristic, and temporary bus-stop creation heuristic.

3.4.1 Heuristic I: Speed limiting bus-holding heuristic

When a bus agent encounters a decreased speed limit on an avenue, due to exogenous events in the network, the following protocol is executed:

1. The bus agent reports the reduced speed to the central control agent.

2. The central control agent notifies other bus agents that the indicated avenue has a decreased speed limit.

3. On the following stop after the affected avenue, buses will be instructed to

perform a bus holding for an amount of time proportional to the speed limit reported (i.e., the lower the speed limit, the longer the holding time).

Figure 3.2 shows how the system responds at upstream and downstream stops based on speed changes.

Figure 3.2: Central control actions in response to reduced speed limits: Heuristic I

When the speed limit returns to normal, the bus agent updates the central control agent, who then informs other agents to normalize their speed parameters.

3.4.2 Heuristic II: Dead-heading level heuristic

The dead-heading level heuristic is used to mitigate the effects of randomness in passenger arrival rate at bus stops. It consists of labeling each bus stop with dead-heading level according to its passenger demand. The dead-heading level indicates the number of buses that must make a skip-stop before the stop can be served. For example, a stop with a dead-heading level of one will be served by a bus only when another bus has previously skipped the stop. Initially, stops are marked with a dead-heading level of zero.

The dead-heading level protocol is as follows when the passenger arrival rate at a bus stop surpasses the usual demand:

1. A bus agent identifies a higher demand at a stop, notifying the central control agent of the situation.

2. In response, the central control agent applies the dead-heading strategy, adjusting each stop's dead-heading level according to demand. The stop with a high passenger rate decreases its dead-heading level by one, while the other stops increase their levels by one.

3. Once bus agents receive the message from the central control agent, they recalculate their intentions to consider the stop with high passenger demand.

Figure 3.3 shows an example of the specific stops to be prioritized based on demand fluctuations, managing bus spacing.

Figure 3.3: Heuristic II: Dead-heading level heuristic adjustments in response to increased passenger arrival rates

3.4.3 Heuristic III: Temporary bus-stop creation heuristic

Exogenous events like bus breakdowns or road accidents can disable bus operations. To simulate such cases, the MAS system allows for establishing a probability of a bus being suspended from the route services for each time unit during the simulation. To account for the random suspension of buses, a new heuristic is introduced. The idea of the new heuristic is to create a temporary bus stop in the public network where the bus is disabled, in order to re-plan the intentions of the rest of the bus agents. The protocol for the heuristic is as follows:

1. When a bus suspends its service on a route, it notifies the central control agent of the situation.

2. The central control agent sends a message to the other bus agents about the suspended bus, and that a temporary stop has been added at the location of the suspended bus. Notice that this temporary stop will not have new passengers arriving, it only contains the stranded passengers from the suspended bus (Figure 3.4).

3. Bus agents recalculate their intentions to consider the new temporary stop (Figure 3.5).

4. If a bus agent satisfies the passenger demand at the temporary stop, it notifies the central control agent about it (Figure 3.6).

5. Once the central control agent receives a message that the demand is satisfied in a temporary stop, it removes it from the route, notifying the network about it to resume planned operations.

Figure 3.4: Visual representation of central control agent actions for heuristic III (1)

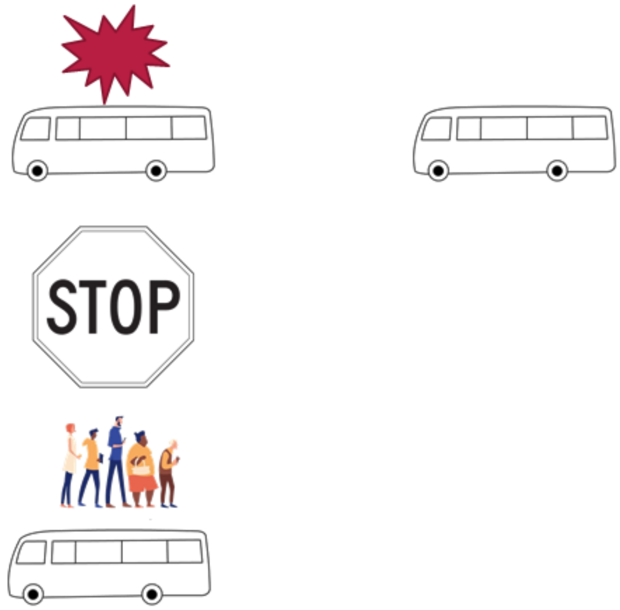

Figure 3.5: Visual representation of central control agent actions for heuristic III (2)

Figure 3.6: Visual representation of central control agent actions for heuristic III (3)

3.5 Mixed-Initiative System

A mixed-initiative system was developed to analyze the impact of human intervention within the system. The mixed-initiative system allows users to input decision-making parameters, simulating human intervention, to control bus spacing and manage disruptions. Figure 3.7 shows the user interface prototype, enabling parameter adjustments such as bus holding time and skip-stop decisions.

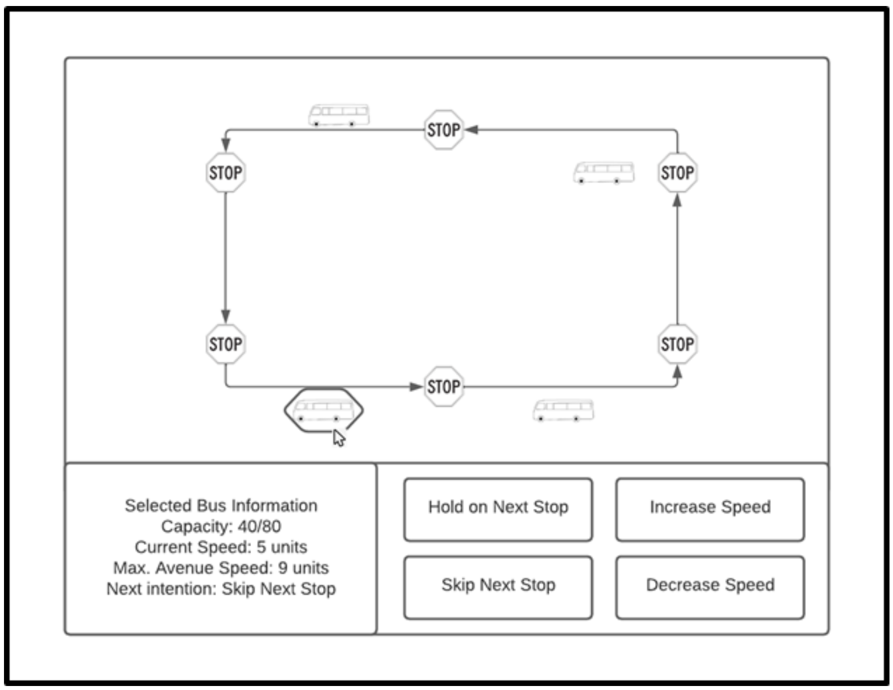

Figure 3.7: User interface proof of concept for mixed-initiative system control.

Furthermore, Figure 3.8 shows the simulator integrated with the Mixed-Initiative system prototype. Notice that the simulator allows users to interact, in real time, with the public transportation system. Users can move forward or backward in time in the simulator, and at the same time enact certain actions for each transportation unit in the network. The simulator provides information on the status of the network regarding the actual capacity of the buses, the number of passengers left at bus stops, actual speeds, and so on; important criteria for making decisions.

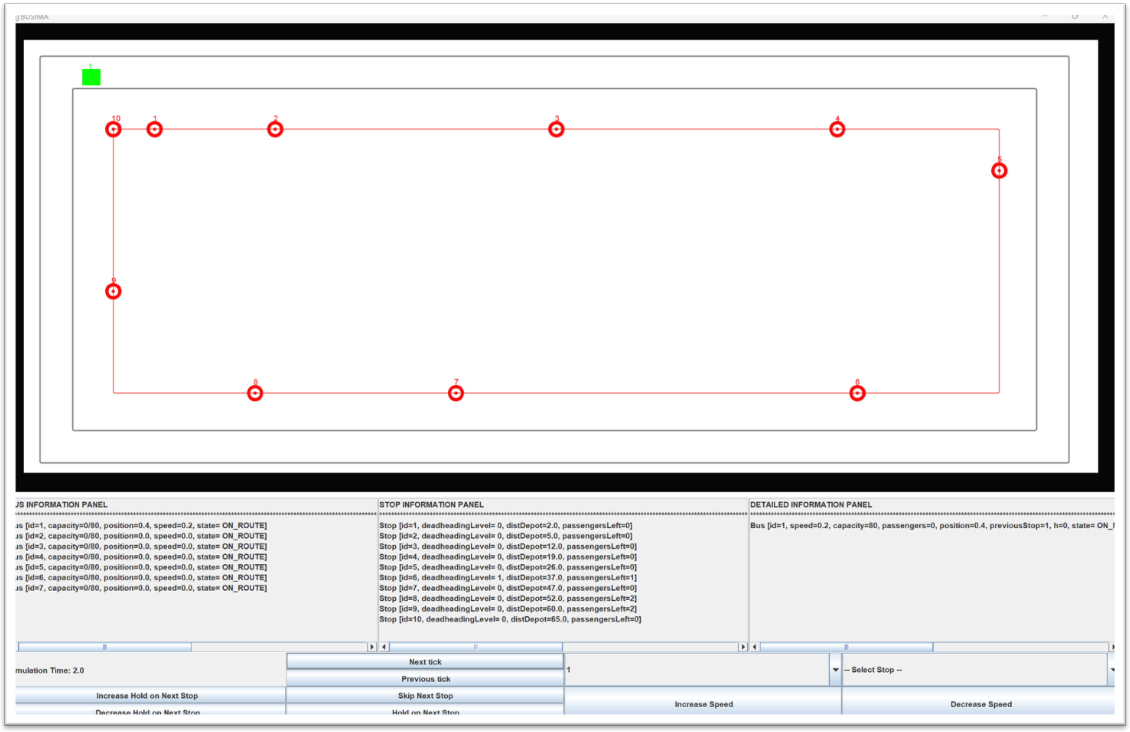

Figure 3.8: Mixed-Initiative Simulator

3.6 Sample Selection

The experiment evaluation includes three sample types: one based on real data from the ECOVIA system and two datasets used in previous studies. The data from ECOVIA system was obtained on 2018. These diverse samples allow us to compare the results of our approach with previous work and to validate the consistency of the proposed solution. The next chapter describes the characteristics of the different datasets that define the public transport networks selected for evaluation.

3.7 Experimental Design

The research questions from Chapter 1 guide the experimental design. Table 3.1 lists the 16 combinations of the independent variables to address the following evaluation categories:

- Performance Difference with/without Exogenous Events: To estimate the impact of exogenous factors on bus bunching and passenger waiting times. Recall, from previous chapters, that the exogenous events considered are: speed limit randomness (SLR), arrival rate randomness (ARR), and Bus Suspension Randomness (BSR).
- System Robustness with Heuristics: To evaluate agent adaptability to exogenous events.
- Effect of Mixed-Initiative System: To examine performance improvements from user intervention.
- Impact of Combined Exogenous Events: To identify which events most affect multi-agent performance.

3.8 Results Analysis

The results, discussed in the next Chapter, will be analyzed using ANOVA to evaluate variance across different experimental conditions, with visualizations showing dependent variable trends across simulations. These analyses provide insights into the effectiveness of the multi-agent system, heuristics, and mixed-initiative system. Minitab stadistic software will be used for ANOVA.

Independent Variables / Experiment	Exogeneous Factors: SLR	Exogeneous Factors: ARR	Exogeneous Factors: BSR	Mixed-Initiative System	Heuristics
1					
2	X	X	X	X	
3	X	X	X		X
4	X	X			X
5	X		X		X
6	X				X
7		X	X		X
8		X			X
9			X		X
10	X	X	X		
11	X	X			
12	X		X		
13	X				
14		X	X		
15		X			
16			X		

Table 3.1: Design of Experiments

Chapter 4

Results and Discussion

This chapter details the results obtained after the empirical evaluation, based on the experimental design described in section 3.7. For each of the 16 experiments, combining the input from the independent variables, 10 evaluation runs were performed, with a significance level of 0.05 for the ANOVA test. The experiments were carried out on a Windows 11 system with i5 11400 processor and 16GB RAM.

Table 4.1 shows the characteristics of the three public transportation networks considered for evaluation. The properties consider the number of stops and buses in the network, the number of calls to the solver, the maximum alighting time for passengers to get off the units, and the dwelling parameter corresponding to the maximum time buses remain in a bus stop.

These networks consider two types of transport services commonly used to study the bus bunching problem: the fixed-route service and the bus rapid transit service (National Center for Mobility Management, 2023). Vehicles run on regularly scheduled routes with fixed stops and no deviation in networks with a fixed-route service. Typically, fixed-route services are characterized by printed schedules or timetables with designated bus stops where passengers alight and board larger transit vehicles. On the other hand, bus-rapid transit networks operate independently from all modes of transportation on an exclusive right-of-way route. It often serves as an express service with a minimal number of stops. ECOVIA, the final network in Table 4.1, can be seen as a bus-rapid transit network that provides services using

Public Transport Properties	Fixed-route Service	Bus rapid Transit	ECOVIA
Stops	10	10	40
Buses	7	7	10
Bus Holding Solver Calls	4	4	15
Bus Alight	0.15	0.15	0.14
Bus Dwell	0.25	0.25	0.14
Overtake	TRUE	FALSE	FALSE
Circular	TRUE	FALSE	FALSE

Table 4.1: Public Transportation Network Properties for Evaluation

an exclusive lane[1]. It is a real bus network containing 40 stations implemented in Monterrey, Mexico.

Table 4.2 shows the empirical evaluation results after averaging 10 simulation runs for each of the 16 simulation scenarios. The table depicts two important metrics involved with the bus bunching problem, the average headway (AH) between a pair of buses in the network (i.e., a distance measure), and the average passenger waiting time (APWT) of users in the network.

4.1 Performance of the MAS in the presence of Exogenous Events

The first research question of this work addresses the difference in performance (bus bunching, passenger waiting time) for the multi-agent system when we consider exogenous events in a simulation environment. We consider experiments 1 and 10 from Table 3.1 to answer this question. Experiment 1 is the baseline in our evaluation since such an experiment does not consider exogenous factors; therefore, it measures

[1] https://metromonterrey.com/ecovia/

Transportation Network	Fixed-route Service		Bus Rapid Transit		ECOVIA	
Experiment	AH	APWT	AH	APWT	AH	APWT
1	0.779	83.79	0.797	82.48	12.04	81.91
2	0.581	89.17	0.787	87.11	12.52	83.07
3	0.807	81.21	0.795	82.75	12.97	83.33
4	0.781	82.49	0.788	81.92	12.21	83.88
5	0.794	81.97	0.790	82.23	12.73	83.65
6	0.786	81.45	0.789	82.69	12.43	83.73
7	0.788	82.71	0.798	82.28	12.15	82.91
8	0.786	81.79	0.788	81.83	12.68	82.18
9	0.787	81.62	0.794	81.36	12.99	83.51
10	0.891	91.71	0.896	92.31	13.88	97.15
11	0.792	82.34	0.797	81.94	12.84	83.08
12	0.786	81.61	0.795	82.71	12.44	82.21
13	0.785	82.47	0.797	82.57	12.69	83.84
14	0.788	81.34	0.789	82.41	0.788	81.34
15	0.789	81.41	0.788	81.67	0.789	81.41
16	0.787	81.94	0.798	81.22	0.787	81.94

Table 4.2: Empirical evaluation results

plain multi-agent system performance without external factors. On the other hand, experiment 10 considers exogenous events to assess their impact on the MAS. In both experiments, there is no support from the mixed-initiative system or the proposed heuristics.

The results, shown in Table 4.2, indicate that there is a significant difference between the means of both experiments once we performed an ANOVA test, which shows that exogenous factors impact the performance of the service of transportation networks. For example, there is an increase in the average passenger waiting time of 9.45% once exogenous factors are introduced for the fixed route service, 11.91% for the rapid transit service bus, and 18.60% for ECOVIA. This is an indication that systems have to take into account external events to provide more robust and reliable solutions.

4.2 Impact of the Mixed-Initiative System in the MAS

The second research question, proposed in this thesis work, is related to estimating the impact of the mixed-initiative system in the MAS. Experiments 2 and 10 are considered. The first experiment includes exogenous events and the mixed-initiative system intervention, while the second one excludes such a system from the MAS.

We can observe, in Table 4.2, that the intervention of experts, through the mixed-initiative system, improves the performance of the MAS when exogenous events are present. Notice that average passenger waiting times are shorter for the three different transportation networks when the MAS is supported by the mixed-initiative system. Users have to wait on average 2.85% longer for the fixed-route service, almost 6% more for the bus rapid service, and a significant 17% increase for the ECOVIA if we do not allow expert intervention through the mixed-initiative system during the decision-making cycle.

4.3 Performance of the MAS in the presence of Exogenous Events when augmented with Heuristics

To answer research question three related to estimating the impact of integrating bus bunching heuristics into the MAS when exogenous events are present, we consider experiments 3 and 10 from our experimental design. Recall that experiment 3 considers the three exogenous factors, analyzed in this thesis, with a MAS integrated with heuristics, while in experiment 10 heuristics are disabled.

Notice that integrating heuristics into the MAS increases the efficiency of the transport networks. In the empirical evaluation, the heuristic-based MAS results in shorter average passenger waiting times for the three transport networks. For example, if we do not consider heuristics, fixed-route service results in 12.93% longer average passenger waiting times, bus rapid service in 11.55%, and ECOVIA in 16.58%; thus justifying heuristic integration.

4.4 Aggregated Impact of Exogenous Events on the MAS

The final question concerns identifying if there is a combination of exogenous events that most affect MAS performance. To answer such a question, the analysis considers experiments 10 to 16 for a MAS without any support, and experiments 3 to 9 for a MAS integrated with heuristics (see Table 3.1). We want to observe whether exogenous events affect a MAS differently when you have heuristic support.

We can observe, in Figure 4.1, that the three exogenous events combined significantly increase the average waiting passenger time (APWT) in the three public transportation networks for the MAS without additional support, ECOVIA being

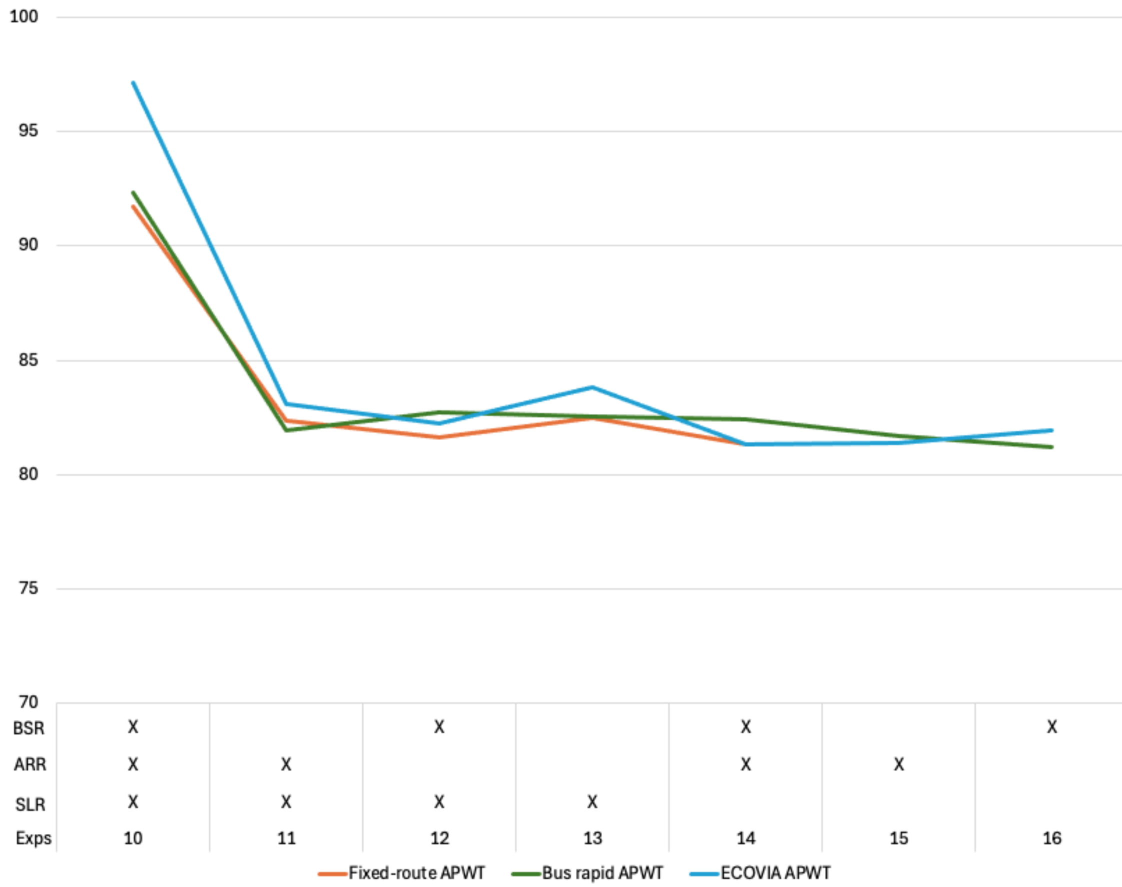

Figure 4.1: Impact of Exogenous Events on APWT in MAS without Support

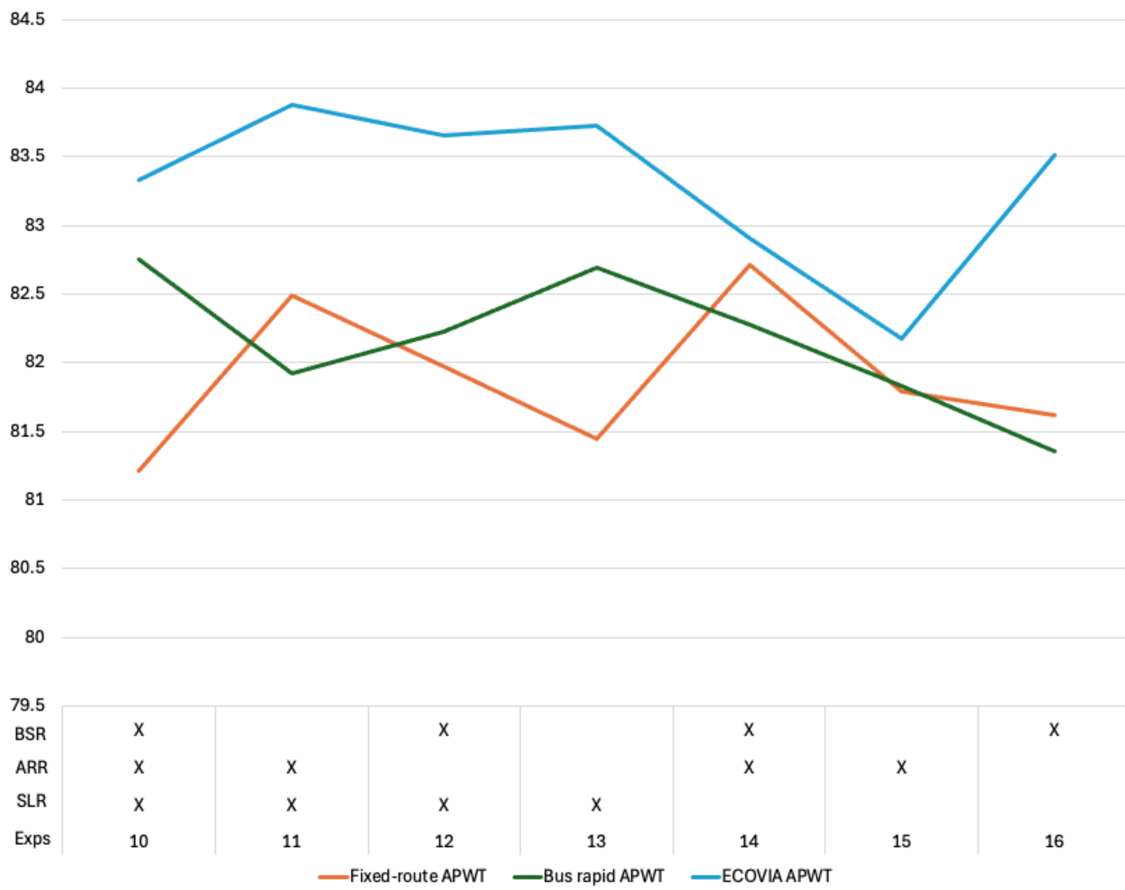

Figure 4.2: Impact of Exogenous Events on APWT in MAS with Heuristic Support

the network that is most affected. Notice that the MAS remains stable for any pairwise combination of exogenous factors. It appears that the Speed Limit Randomness (SLR) factor in isolation tends to slightly affect more of the three networks.

Figure 4.2 shows the results of combining external events for the MAS with heuristic support. First, we can observe that ECOVIA is the public network that results in larger APWTs, which is equivalent to the behavior of the MAS without support. However, this time, combining the three external factors does not always result in larger APWTs, implying that heuristics play a role in keeping networks more robust to external events. For example, it is interesting that for the Fixed-route service, combining the three factors or evaluating each factor individually, results in better APWTs than any pairwise combination of them.

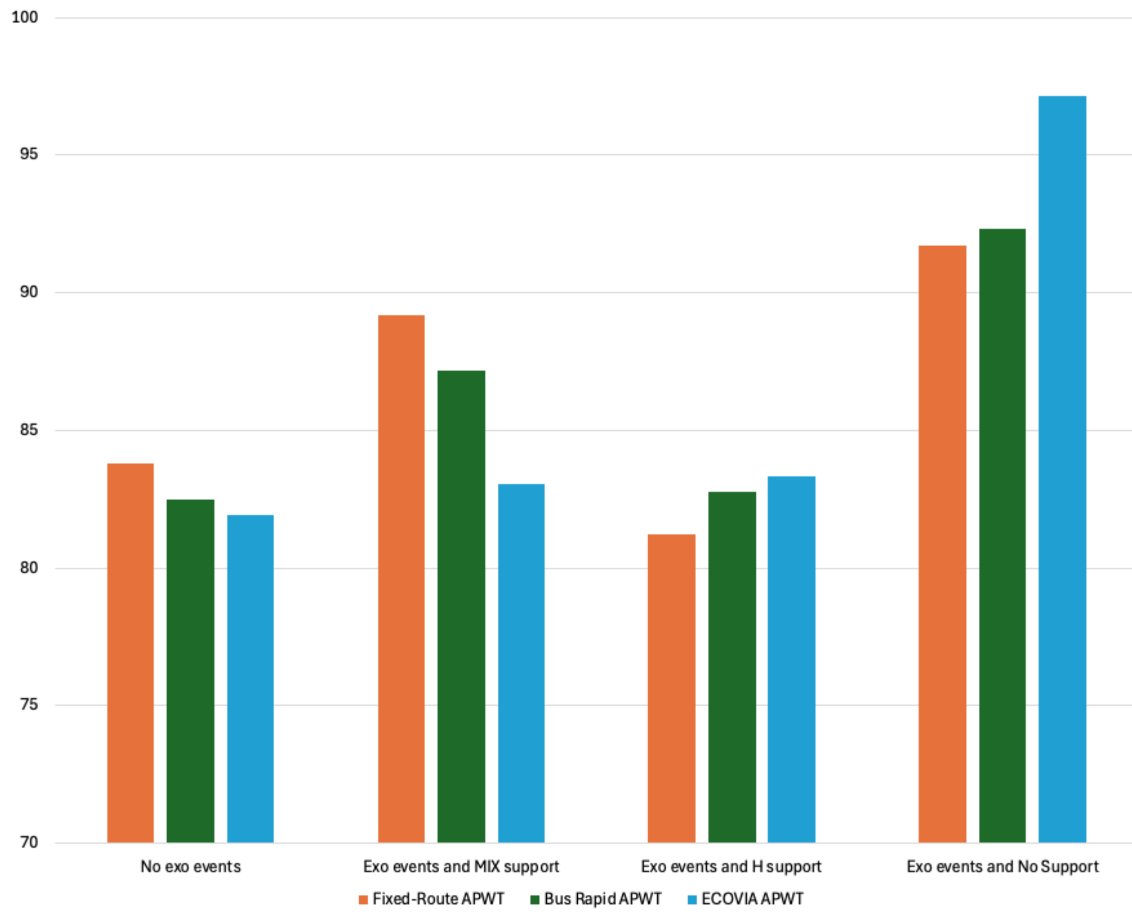

Figure 4.3: Global Results on main MAS Configurations

Finally, Figure 4.3 shows a summary of the main results for the three public networks under different evaluation configurations. The leftmost column shows the behavior of the MAS when there are no exogenous events; as expected, the APWTs are smaller than the rightmost column, which includes such external factors but without any support for the system.

Once we introduce mixed-initiative support (MIX) and heuristics, the MAS will reduce the average passenger waiting times, proving the value of the interventions. The fully automated system, augmented with heuristics, shows better APWT performance than considering a human expert in the loop. Further work will elaborate on these findings to integrate human experts and artificial intelligence agents to work in coordination on the bus-bunching problem.

Chapter 5

Conclusions

The research presented in this thesis aimed to address the bus-bunching problem through the design and implementation of a Multi-Agent System (MAS) integrated with heuristic algorithms and a mixed-initiative approach. The proposed system, BUSIMA, was evaluated in simulated scenarios reflecting real-world complexities, including exogenous events such as varying traffic conditions, passenger arrival rates, and speed limitations. The findings demonstrate significant advancements in public transportation efficiency, validating the contributions made through this research.

5.1 Key Findings

5.1.1 Impact of Exogenous Events

The presence of exogenous events significantly increases the challenges associated with maintaining bus schedules. The simulation results indicate that without any system support, average passenger waiting times (APWT) increase notably, particularly for high-density networks like ECOVIA.

The integration of heuristics within the MAS reduced APWT and improved route efficiency by adapting dynamically to these external factors. This robustness highlights the effectiveness of the proposed system.

5.1.2 Heuristic Contributions

Three specific heuristics were developed and validated:

1. Speed Limiting Bus-Holding: Controlled bus speeds to maintain equitable headways.
2. Dead-Heading Level Adjustments: Optimized bus deployment based on passenger density.
3. Temporary Bus Stop Creation: Improved passenger access in high-demand areas.

These heuristics contributed to an average reduction in APWT by up to 14.22% in ECOVIA, 10.35% in Fixed-route service, and 11.44% in Bus Rapid Transit compared to scenarios without support.

5.1.3 Mixed-Initiative System

The inclusion of a Mixed-initiative system allowed human experts to intervene in decision-making. While the fully automated MAS, integrated with heuristics, demonstrated superior performance in terms of APWT, the mixed-initiative approach provides flexibility for human judgment integration in complex or unforeseen scenarios and shows better performance than the MAS without support.

5.2 Contributions

This thesis provides three significant contributions to the domain of intelligent transportation systems:

1. Definition of Exogenous Factors: Three critical exogenous factors (speed randomness, variable passenger arrival rates, and random bus breakdowns) were

identified, and their impact on bus route performance was quantified.

2. Development of Adaptive Heuristics: Heuristic algorithms were designed to enable the MAS to adapt effectively to exogenous disturbances, ensuring improved stability and efficiency in public transportation systems.

3. Development of Mixed-Initiative System: A MIX system was developed through a simulation environment to capture human expert intervention on public transportation networks.

5.3 Future Work

Several avenues for further exploration and enhancement of the proposed system have been identified:

1. Interface Improvements: Enhance the simulation interface to allow reversal to previous ticks, enabling more detailed scenario analysis and decision-making. Implement save-and-load functionality for simulation instances to facilitate peer review and collaborative scenario testing.

2. Integration of Additional Strategies: Explore recently developed strategies, such as short-turning mechanisms, where buses skip certain stops to better serve high-demand areas. These could complement existing heuristics and further reduce bus bunching.

3. Real-World Deployment: Conduct pilot implementations of BUSIMA in real public transportation networks, such as ECOVIA, to validate its efficacy under real-world conditions. Insights from such deployments could reveal new challenges and opportunities for system refinement.

4. Human-Agent Coordination: Expand research on the coordination between human experts and AI agents, aiming to optimize the balance between automated decision-making and human intervention.

The findings of this thesis underscore the potential of MAS and heuristic algorithms in mitigating exogenous events for the bus-bunching problem, even in the face of complex, real-world challenges. The robust performance of BUSIMA highlights its viability as a practical solution for public transportation systems, with the flexibility to incorporate human expertise. Future work will aim to build on these foundations, advancing the field of intelligent transportation systems and improving urban mobility for diverse populations.

Bibliography

Abramson, G. (2006). Introducción a la teoría de juegos. *Bariloche: Centro Atómico Bariloche*.

Adebisi, O. (1986). A mathematical model for headway variance of fixed-route buses. *Transportation Research Part B: Methodological*, 20(1):59–70.

Allen, J. E., Guinn, C. I., and Horvtz, E. (1999). Mixed-initiative interaction. *IEEE Intelligent Systems and their Applications*, 14(5):14–23.

Alon, N. and Spencer, J. H. (2015). *The probabilistic method*. John Wiley & Sons.

Ampountolas, K. and Kring, M. (2020). Mitigating bunching with bus-following models and bus-to-bus cooperation. *IEEE Transactions on Intelligent Transportation Systems*, 22(5):2637–2646.

Andréasson, N., Evgrafov, A., and Patriksson, M. (2020). *An introduction to continuous optimization: foundations and fundamental algorithms*. Courier Dover Publications.

Andres, M. and Nair, R. (2017). A predictive-control framework to address bus bunching. *Transportation Research Part B: Methodological*, 104:123–148.

APTA (2023). Public Transportation Facts.

Arriagada, J., Gschwender, A., Munizaga, M. A., and Trépanier, M. (2019). Modeling bus bunching using massive location and fare collection data. *Journal of Intelligent Transportation Systems*, 23(4):332–344.

Avenali, A., Catalano, G., Gregori, M., and Matteucci, G. (2020). Rail versus bus local public transport services: A social cost comparison methodology. *Transportation Research Interdisciplinary Perspectives*, 7:100200.

Baimbetova, A., Konyrova, K., Zhumabayeva, A., and Seitbekova, Y. (2021). Bus arrival time prediction: a case study for almaty. In *2021 IEEE International Conference on Smart Information Systems and Technologies (SIST)*, pages 1–6.

Balagurusamy, E. (2008). *Object Oriented Programming With C++*. McGraw-Hill Education (India) Pvt Limited.

Barnett, A. (1974). On controlling randomness in transit operations. *Transportation Science*, 8(2):102–116.

Berrebi, S. J., Hans, E., Chiabaut, N., Laval, J. A., Leclercq, L., and Watkins, K. E. (2018). Comparing bus holding methods with and without real-time predictions. *Transportation Research Part C: Emerging Technologies*, 87:197–211.

Bian, B., Zhu, N., and Meng, Q. (2023). Real-time cruising speed design approach for multiline bus systems. *Transportation research part B: methodological*, 170:1–24.

Bian, B., Zhu, N., Pinedo, M., Ma, S., and Yu, Q. (2020). An optimization-based speed-control method for high frequency buses serving curbside stops. *Transportation Research Part C: Emerging Technologies*, 121:102860.

Bond, A. H. and Gasser, L. (2014). *Readings in distributed artificial intelligence*. Morgan Kaufmann.

Bordini, R. H., Hübner, J. F., and Wooldridge, M. (2007). *Programming multi-agent systems in AgentSpeak using Jason*, volume 15. John Wiley & Sons.

Cats, O. and Gkioulou, Z. (2017). Modeling the impacts of public transport reliability and travel information on passengers' waiting-time uncertainty. *EURO Journal on Transportation and Logistics*, 6(3):247–270.

Chanel, C. P., Roy, R. N., Drougard, N., and Dehais, F. (2020). Mixed-initiative human-automated agents teaming: towards a flexible cooperation framework. In *Engineering Psychology and Cognitive Ergonomics. Cognition and Design: 17th International Conference, EPCE 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part II 22*, pages 117–133. Springer.

Chen, W., Zhang, H., Chen, C., and Wei, X. (2021). An integrated bus holding and speed adjusting strategy considering passenger's waiting time perceptions. *Sustainability*, 13(10):5529.

Chen, W., Zhou, K., and Chen, C. (2016). Real-time bus holding control on a transit corridor based on multi-agent reinforcement learning. In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pages 100–106. IEEE.

Chioni, E., Iliopoulou, C., Milioti, C., and Kepaptsoglou, K. (2020). Factors affecting bus bunching at the stop level: A geographically weighted regression approach. *International Journal of Transportation Science and Technology*, 9(3):207–217.

Comi, A., Sassano, M., and Valentini, A. (2022). Monitoring and controlling real-time bus services: A reinforcement learning procedure for eliminating bus bunching. *Transportation Research Procedia*, 62:302–309.

de Souza, F. and Teixeira Sebastiani, M. (2021). Improving resilience of bus bunching holding strategy through a rolling horizon approach. *Journal of Transportation Engineering, Part A: Systems*, 147(10):04021074.

Deng, Y., Luo, X., Hu, X., Ma, Y., and Ma, R. (2020). Modeling and prediction of bus operation states for bunching analysis. *Journal of Transportation Engineering, Part A: Systems*, 146(9):04020106.

Du, B. and Dublanche, P.-A. (2018). Bus bunching identification using smart card data. In *2018 IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS)*, pages 1087–1092. IEEE.

Durfee, E. H. and Rosenschein, J. S. (1994). Distributed problem solving and multi-agent systems: Comparisons and examples. In *Proceedings of the Thirteenth International Distributed Artificial Intelligence Workshop*, pages 94–104.

Eberlein, X. J., Wilson, N. H., Barnhart, C., and Bernstein, D. (1998). The real-time deadheading problem in transit operations control. *Transportation Research Part B: Methodological*, 32(2):77–100.

Enayatollahi, F., Idris, A. O., and Atashgah, M. A. (2019). Modelling bus bunching under variable transit demand using cellular automata. *Public Transport*, 11(2):269–298.

Feng, S., Sun, X., and Wang, D. (2016). The analysis and application of competition and cooperation between the bus lines. *KSCE Journal of Civil Engineering*, 20:1540–1545.

Ferber, J., Gutknecht, O., and Michel, F. (2003). From agents to organizations: an organizational view of multi-agent systems. In *International workshop on agent-oriented software engineering*, pages 214–230. Springer.

Fu, L., Liu, Q., and Calamai, P. (2003). Real-time optimization model for dynamic scheduling of transit operations. *Transportation research record*, 1857(1):48–55.

Gershenson, C. and Pineda, L. A. (2009). Why does public transport not arrive on time? the pervasiveness of equal headway instability. *PLOS ONE*, 4(10):1–15.

Ghallab, M., Nau, D., and Traverso, P. (2004). *Automated Planning: theory and practice*. Elsevier.

Gong, Z., Du, B., Liu, Z., Zeng, W., Perez, P., and Wu, K. (2020). Sd-seq2seq : A deep learning model for bus bunching prediction based on smart card data. In *2020 29th International Conference on Computer Communications and Networks (ICCCN)*, pages 1–9.

He, S.-X., Liang, S.-D., Dong, J., Zhang, D., He, J.-J., and Yuan, P.-C. (2020). A holding strategy to resist bus bunching with dynamic target headway. *Computers & Industrial Engineering*, 140:106237.

Hernández-Landa, L. G., Morales-Marroquín, M. L., Nigenda, R. S., and Ríos-Solís, Y. Á. (2015). Linear bus holding model for real-time traffic network control. In *Applied Simulation and Optimization: In Logistics, Industrial and Aeronautical Practice*, pages 303–319. Springer.

Hickman, M. D. (2001). An analytic stochastic model for the transit vehicle holding problem. *Transportation Science*, 35(3):215–237.

Horling, B. and Lesser, V. (2004). A survey of multi-agent organizational paradigms. *The Knowledge Engineering Review*, 19(4):281–316.

Huang, Y., Chen, C., Su, Z., Chen, T., Sumalee, A., Pan, T., and Zhong, R. (2021). Bus arrival time prediction and reliability analysis: An experimental comparison of functional data analysis and bayesian support vector regression. *Applied Soft Computing*, 111:107663.

Ignall, E. and Kolesar, P. (1974). Optimal dispatching of an infinite-capacity shuttle: Control at a single terminal. *Operations Research*, 22(5):1008–1024.

Iliopoulou, C., Milioti, C., Vlahogianni, E., Kepaptsoglou, K., and Sánchez-Medina, J. (2018). The bus bunching problem: Empirical findings from spatial analytics. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 871–876. IEEE.

Iliopoulou, C., Vlahogianni, E. I., and Kepaptsoglou, K. (2020a). Understanding the factors that affect the bus bunching events' duration. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE.

Iliopoulou, C. A., Milioti, C. P., Vlahogianni, E. I., and Kepaptsoglou, K. L. (2020b).

Identifying spatio-temporal patterns of bus bunching in urban networks. *Journal of Intelligent Transportation Systems*, 24(4):365–382.

Kaddoura, I., Kickhöfer, B., Neumann, A., and Tirachini, A. (2015). Agent-based optimisation of public transport supply and pricing: impacts of activity scheduling decisions and simulation randomness. *Transportation*, 42:1039–1061.

Kieu, L.-M., Bhaskar, A., and Chung, E. (2016). Insights into the bus bunching problem: a multi-agent simulation approach. Technical report.

Koppisetti, M. V., Kavitha, V., and Ayesta, U. (2018). Bus schedule for optimal bus bunching and waiting times. In *2018 10th International Conference on Communication Systems & Networks (COMSNETS)*, pages 607–612. IEEE.

Kumarswamy, S. (2020). Usability in mixed initiative systems. In *HCI International 2020-Late Breaking Papers: Multimodality and Intelligence: 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings 22*, pages 495–504. Springer.

Li, M. and Li, Y. (2022). Bus predictive-control method considering the impact of traffic lights. *Journal of Advanced Transportation*, 2022(1):5280109.

Liang, S., He, S., Zhang, H., and Ma, M. (2021). Optimal holding time calculation algorithm to improve the reliability of high frequency bus route considering the bus capacity constraint. *Reliability Engineering & System Safety*, 212:107632.

Liang, S. and Ma, M. (2019). Analysis of bus bunching impact on car delays at signalized intersections. *KSCE Journal of Civil Engineering*, 23:833–843.

Liu, Q., Xiao, M., Ming, X., and Huang, H. (2022a). Multi-class identification of urban bus bunching rate based on xgboost. In *International Conference on Smart Transportation and City Engineering (STCE 2022)*, volume 12460, pages 915–921. SPIE.

Liu, Y., Luo, X., Cheng, S., Yu, Y., Tang, J., and Shang, X. (2022b). Comparison of two algorithms for multiline bus dynamic dispatching. *Discrete Dynamics in Nature and Society*, 2022(1):2086717.

Ma, Q., Li, S., Zhang, H., Yuan, Y., and Yang, L. (2021). Robust optimal predictive control for real-time bus regulation strategy with passenger demand uncertainties in urban rapid transit. *Transportation Research Part C: Emerging Technologies*, 127:103086.

Marion, G., . L. D. (2008). An introduction to mathematical modelling.

Mendenhall III, W., Beaver, R. J., and Beaver, B. M. (2007). Probabilidad y estadística.

Moreira-Matias, L., Cats, O., Gama, J., Mendes-Moreira, J., and De Sousa, J. F. (2016). An online learning approach to eliminate bus bunching in real-time. *Applied Soft Computing*, 47:460–482.

Moreira-Matias, L., Gama, J., Mendes-Moreira, J., and Freire de Sousa, J. (2014). An incremental probabilistic model to predict bus bunching in real-time. In *Advances in Intelligent Data Analysis XIII: 13th International Symposium, IDA 2014, Leuven, Belgium, October 30–November 1, 2014. Proceedings 13*, pages 227–238. Springer.

National Center for Mobility Management (2023). Public Transportation Terms.

Neumann, A. and Nagel, K. (2010). Avoiding bus bunching phenomena from spreading: A dynamic approach using a multi-agent simulation framework. *VSP WorkingPaper10-08, TU Berlin, Transport Systems Planning and Transport Telematics. See www. vsp. tu-berlin. de/publications.*

Newell, G. F. and Potts, R. B. (1964). Maintaining a bus schedule. In *Australian Road Research Board (ARRB) Conference, 2nd, 1964, Melbourne*, volume 2.

Nguyen-Phuoc, D. Q., Young, W., Currie, G., and De Gruyter, C. (2020). Traffic congestion relief associated with public transport: state-of-the-art. *Public Transport*, 12(2):455–481.

Olvera Toscano, C. M. (2018). *Modelo matemático e implementación de un simulador basado en un sistema de transporte urbano.* PhD thesis, Universidad Autónoma de Nuevo León.

Padgham, L. and Winikoff, M. (2005). *Developing intelligent agent systems: A practical guide*. John Wiley & Sons.

Pan, L., Zhou, Y., Meng, Q., and Wang, Y. (2023). Impact analysis of traffic factors on urban bus bunching. *IEEE Intelligent Transportation Systems Magazine*, 15(5):6–24.

Patlán Castillo, J. Á. (2020). *Solving the Bus Bunching Problem with a Multiagent System*. PhD thesis, Universidad Autónoma de Nuevo León.

Petit, A., Lei, C., and Ouyang, Y. (2019). Multiline bus bunching control via vehicle substitution. *Transportation Research Part B: Methodological*, 126:68–86.

Petit, A., Ouyang, Y., and Lei, C. (2018). Dynamic bus substitution strategy for bunching intervention. *Transportation Research Part B: Methodological*, 115:1–16.

Quek, W. L., Chung, N. N., Saw, V.-L., and Chew, L. Y. (2021). Analysis and simulation of intervention strategies against bus bunching by means of an empirical agent-based model. *Complexity*, 2021(1):2606191.

Rashidi, S., Ranjitkar, P., Csaba, O., and Hooper, A. (2017). Using automatic vehicle location data to model and identify determinants of bus bunching. *Transportation research procedia*, 25:1444–1456.

Rezazada, M., Nassir, N., Tanin, E., and Ceder, A. (2024). Bus bunching: a comprehensive review from demand, supply, and decision-making perspectives. *Transport Reviews*, pages 1–25.

Rosenschein, J. S. and Zlotkin, G. (1994). *Rules of encounter: designing conventions for automated negotiation among computers*. MIT press.

Ross, S. M. (2022). *Simulation*. academic press.

Russell, S. J. and Norvig, P. (2016). *Artificial intelligence: a modern approach*. Pearson.

Shan, X., Wang, C., and Zhou, D. (2023). Interfering spatiotemporal features and causes of bus bunching using empirical gps trajectory data. *Journal of Grid Computing*, 21(1):15.

Shoham, Y. (1993). Agent-oriented programming. *Artificial intelligence*, 60(1):51–92.

Smith, R. W. (1994). Spoken variable initiative dialog: An adaptable natural-language interface. *IEEE Expert*, 9(1):45–50.

Suh, W., Chon, K.-S., and Rhee, S.-M. (2002). Effect of skip-stop policy on a korean subway system. *Transportation Research Record*, 1793(1):33–39.

Sun, A. and Hickman, M. (2005). The real–time stop–skipping problem. *Journal of Intelligent Transportation Systems*, 9(2):91–109.

Sun, W. (2020). Bus bunching prediction and transit route demand estimation using automatic vehicle location data.

Sun, W. and Schmöcker, J.-D. (2018). Considering passenger choices and overtaking in the bus bunching problem. *Transportmetrica B: Transport Dynamics*, 6(2):151–168.

Sycara, K. P. (1998). Multiagent systems. *AI magazine*, 19(2):79–79.

Tian, S. (2021). A short-turning strategy for the management of bus bunching considering variable spatial-temporal running time. *Journal of Uncertain Systems*, 14(03):2150020.

Tirachini, A., Godachevich, J., Cats, O., Muñoz, J. C., and Soza-Parra, J. (2022). Headway variability in public transport: A review of metrics, determinants, effects for quality of service and control strategies. *Transport Reviews*, 42(3):337–361.

Torreno, A., Onaindia, E., Komenda, A., and Štolba, M. (2017). Cooperative multi-agent planning: A survey. *ACM Computing Surveys (CSUR)*, 50(6):1–32.

Tsoi, K. H. and Loo, B. P. (2022). Bus bunching from a stop-based perspective: insights from visual analytics. In *Proceedings of the Institution of Civil Engineers-Municipal Engineer*, volume 175, pages 2–15. Thomas Telford Ltd.

Vismara, L., Saw, V.-L., and Chew, L. Y. (2021). Bunching dynamics of buses in a loop. In *International Conference on Intelligent Transportation Engineering*, pages 203–212. Springer.

Vismara, L., Saw, V.-L., and Chew, L. Y. (2022). Synchronising bus bunching to the spikes in service demand reduces commuters' waiting time. *Complexity*, 2022(1):8996439.

Walker, M. and Whittaker, S. (1995). Mixed initiative in dialogue: An investigation into discourse segmentation. *arXiv preprint cmp-lg/9504007*.

Walton, D. (2005). *Fundamentals of critical argumentation*. Cambridge University Press.

Wang, J. and Sun, L. (2020). Dynamic holding control to avoid bus bunching: A multi-agent deep reinforcement learning framework. *Transportation Research Part C: Emerging Technologies*, 116:102661.

Wang, J. and Sun, L. (2021). Reducing bus bunching with asynchronous multi-agent reinforcement learning. *arXiv preprint arXiv:2105.00376*.

Wang, P., Chen, X., Chen, W., Cheng, L., and Lei, D. (2018). Provision of bus real-time information: Turning passengers from being contributors of headway irregularity to controllers. *Transportation Research Record*, 2672(8):143–151.

Wang, P., Chen, X., Zheng, Y., Cheng, L., Wang, Y., and Lei, D. (2021). Providing real-time bus crowding information for passengers: A novel policy to promote high-frequency transit performance. *Transportation Research Part A: Policy and Practice*, 148:316–329.

Wang, X. (2022). Integrating conventional headway control with reinforcement learning to avoid bus bunching. *arXiv preprint arXiv:2210.00201*.

Wang, Z., Jiang, R., Jiang, Y., Gao, Z., and Liu, R. (2024). Modelling bus bunching along a common line corridor considering passenger arrival time and transfer choice under stochastic travel time. *Transportation Research Part E: Logistics and Transportation Review*, 181:103378.

Weigand, H. and Dignum, V. (2004). I am autonomous, you are autonomous. In *Agents and Computational Autonomy: Potential, Risks, and Solutions 1*, pages 227–236. Springer.

Weiss, G. (1999). *Multiagent systems: a modern approach to distributed artificial intelligence*. MIT press.

Welding, P. (1957). The instability of a close-interval service. *Journal of the operational research society*, 8(3):133–142.

Weyns, D., Omicini, A., and Odell, J. (2007). Environment as a first class abstraction in multiagent systems. *Autonomous agents and multi-agent systems*, 14:5–30.

Wu, W., Liu, R., and Jin, W. (2017). Modelling bus bunching and holding control with vehicle overtaking and distributed passenger boarding behaviour. *Transportation Research Part B: Methodological*, 104:175–197.

Xin, Q., Fu, R., Yu, S., Ukkusuri, S. V., and Jiang, R. (2021). Modeling bus bunching and anti-bunching control accounting for signal control and passenger swapping behavior. *Journal of Public Transportation*, 23(1):31–62.

Yang, J., Zhou, H., Chen, X., and Cheng, L. (2019). Applying the support vector machine to predicting headway-based bus bunching. In *CICTP 2019*, pages 1542–1553.

Yang, Y., Cheng, J., and Liu, Y. (2024). An overview of solutions to the bus bunching problem in urban bus systems. *Frontiers of Engineering Management*, pages 1–15.

Yokoo, M., Durfee, E. H., Ishida, T., and Kuwabara, K. (1998). The distributed constraint satisfaction problem: Formalization and algorithms. *IEEE Transactions on knowledge and data engineering*, 10(5):673–685.

Zhang, H., Liang, S., Han, Y., Ma, M., and Leng, R. (2020). A prediction model for bus arrival time at bus stop considering signal control and surrounding traffic flow. *IEEE Access*, 8:127672–127681.

Zhao, J., Dessouky, M., and Bukkapatnam, S. (2006). Optimal slack time for schedule-based transit operations. *Transportation Science*, 40(4):529–539.

Zhao, S., Lu, C., Liang, S., and Liu, H. (2016). A self-adjusting method to resist bus bunching based on boarding limits. *Mathematical Problems in Engineering*, 2016(1):8950209.

Zhou, L., Wang, Y., and Cui, H. (2017). The bus auxiliary driving system based on multi-agent strategy. *J. Softw.*, 12(9):722–731.

Ficha autobiográfica

Jesús Ángel Patlán Castillo

Candidato para el grado de Doctorado en Ingeniería
con Orientación en Tecnologías de la Información

Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Tesis:

Heuristics and Mixed-Initiative System in a Multiagent System to reduce Bus Bunching considering Exogenous Factors

Nací el 28 de diciembre de 1995 en Monterrey, Nuevo León. Soy egresado de la carrera de ingeniero administrador de sistemas y de la maestría en ciencias de la ingeniería en sistemas de la Facultad de Ingeniería Mecánica y Eléctrica, y curse diez semestres la licenciatura en matemáticas en la Facultad de Ciencias Físico Matemáticas. Mis intereses principales van por la rama de las matemáticas, con un gusto en particular en materias de algebra abstracta; y también tengo el gusto por el área de la inteligencia artificial en sistemas multiagentes, la cual es la rama a la que dedico mis estudios.