Uber Meets Bus: A Simulation Study of Public Ride-hailing Service

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Kimon E. Swanson

August 2024

dedication...

Acknowledgments

I would like to extend my heartfelt thanks to my brother, Colter Swanson, for his unwavering support and encouragement throughout this whole program. His presence and love have been indispensable to my progress.

Additionally, I wish to acknowledge the numerous contributions from various collaborators and unconventional perspectives that have enriched this study. Previous works have demonstrated that incorporating diverse viewpoints can lead to unexpectedly valuable insights [43]. This research has benefited greatly from such an inclusive approach.

Abstract

To prepare for the future of mobility in areas with widespread infrastructure, it is essential to address the shortcomings of public transit systems that fail to effectively serve their inhabitants' needs due to a lack of optimization. In this study, we developed a simulation solution-based approach to help decision-makers build an efficient and low-cost public transit system for widespread cities backed by data. This is accomplished by implementing a dial-a-ride service to increase versatility and scope of rides. The simulation solution strategy utilizes agent-based modeling, which is executed in real-time in response to stochastic ride requests, thereby generating numerous individual dial-a-ride scenarios to identify the most efficient outcome. Using this simulation, cities will be able to develop a plan to prepare for the future of mobility within their city limits. Knoxville Area Transit (KAT) is being used as a case study to gather real-world insight and data to better our understanding of already-in-place systems.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Public transit systems are an essential component of modern urban infrastructure and have been the subject of extensive scholarly research for decades. Public transit systems play a critical role in facilitating urban mobility, allowing individuals to access essential services and travel to their daily destinations. Despite their widespread use, however, a careful analysis of these systems reveals persistent inefficiency and under-utilization issues. The damaging effects of the aforementioned inefficiencies and under-utilization are two-fold: they lead to substantial economic costs in terms of both lost customer time and public expenditure [93]. The consequences of public transit inefficiencies are not limited to mere economic costs, as they often result in a significant shift in transportation mode for affected individuals. Given the choice of public vs private transportation, most will choose to drive themselves to avoid public transit inefficiencies [13]. The consequences of the previously mentioned shift in transportation modes are not confined to individual commuters, as they have wider implications for traffic congestion and environmental pollution. The increase in private vehicle usage exacerbates traffic congestion, leading to increased emissions and further amplifying existing environmental challenges.

Moreover, for public transportation, i.e. buses, the influx of additional vehicles on the road can lead to a strain on system reliability and efficiency, ultimately resulting in a vicious cycle that can undermine the viability of public transit systems. Given the stochastic nature of bus schedules in conjunction with traffic, addressing the inefficiencies and challenges facing public transit systems is a complex and multifaceted problem that defies easy resolution.

In this study, we will be exploring a simulation-based approach to design a public transit system that is cost-effective while also enhancing accessibility, customer satisfaction, and environmental sustainability. The proposed system consists of a static bus route and a dial-a-ride service that serves passengers with limited accessibility. This study presents an in-depth analysis of two different public transit system scenarios aimed at improving efficiency and accessibility. The first scenario involves a static system with buses following pre-determined routes, based on a case study of the Knoxville Area Transit (KAT), this will be the baseline. The second scenario includes two subsets that adopt an uber-like system, with the first subset utilizing a First-in-First-out (FIFO) system to transport passengers to a drop-off hub and the second subset utilizing a multi-passenger optimized route to drop off passengers at different locations. In the following section, we will delve into a selection of tools and approaches that are designed for modeling and investigating complex systems, providing a foundation for a thorough exploration and optimization of the public transit scenarios proposed.

In response to these challenges, this study proposes a simulation-based approach to design a cost-effective public transit system that prioritizes accessibility, customer satisfaction, and environmental sustainability. The study explores two scenarios, comparing a traditional static bus route with a dial-a-ride service to innovative Uber-like systems with optimized routing strategies. The goal is to provide insights and solutions that contribute to the optimization of public transit systems, acknowledging their broader societal impact beyond mere economic considerations.

1.1 Tools for Modeling Complex Systems

The emergence of advanced simulation software has revolutionized the ability of researchers to model complex situations and relationships, providing them with a valuable new tool. Notably, Anylogic and Flexsim are two highly-regarded simulation software that has introduced novel simulation models previously deemed impossible [6]. These software tools have brought about significant computational power and have simplified the implementation of intricate models, including Agent-Based Modelling (ABM) [40]. ABM, a simulation model that seeks to represent interactions and relationships between different entities or agents, has resulted in a more precise representation of complex systems [67]. ABM enables the researcher to create a representation of complex interactions that might have otherwise been overlooked, providing researchers with a more comprehensive understanding of the system. Through the utilization of such techniques, Fu [35] was able to obtain a profound comprehension of the system under investigation and suggest novel strategies based on precise representations of the system.

The utilization of simulation has started allowing for the optimization of complex algorithms such as the traveling salesman algorithm [85]. This simulation approach aims to efficiently allocate rides and plan routes, with the ultimate goal of reducing both the time and resources needed to complete the transportation service. By incorporating stochastic ride requests and conducting the simulation in real-time, the algorithm evaluates each potential solution and provides immediate feedback to the driver, allowing for quick and effective decision-making. While the approach has shown great promise in improving the efficiency of ride allocation and routing, further research is necessary to evaluate its effectiveness in a variety of real-world scenarios. Future studies should aim to investigate the impact of various factors, such as traffic patterns and road conditions, on the overall effectiveness of the approach.

1.2 Impact

The primary objective of this research is to optimize rides for users and minimize costs in public transport systems. Additionally, this study recognizes the significance of creating a positive impact on the environment. While most public transport systems inherently contribute to a reduction in emissions through a decrease in the number of vehicles on the road, further efforts can be made to increase their ecological sustainability. The adoption of electric rail cars and buses in a number of cities has facilitated a path toward carbon neutrality in the public transit sector, but such initiatives have only been implemented in a limited number of locations [54]. In order to achieve broader adoption, government grants are essential to enable cities to make the necessary changes to their public transit systems. Additionally, the electricity used to power electric public transport must come from renewable sources such as wind, solar, or hydro. For instance, the newly adopted electric buses in Knoxville utilize the power of solar panels to charge their batteries in an eco-friendly manner [52]. Such environmentally conscious modifications yield significant reductions in carbon emissions.

The analysis of the environmental impact of public transport systems presented in this research highlights the potential of sustainable solutions in optimizing rides and minimizing costs for users. While existing public transport systems inherently contribute to emission reduction, further efforts to enhance ecological sustainability are required [50]. The implementation of electric rail cars and buses in select cities showcases the potential of adopting carbon-neutral solutions in the public transit sector. However, their limited adoption calls for an in-depth investigation of the challenges and opportunities associated with scaling these initiatives.

Acknowledging the significant role of government grants in supporting the widespread adoption of electric public transport systems is essential [61]. Financial support can help cities overcome the barriers to entry and implement necessary changes in their transit infrastructure [42]. This, in turn, would contribute to the realization of broader environmental goals, including the reduction of carbon emissions.

Additionally, ensuring that the electricity used to power electric public transport comes from renewable energy sources is a vital aspect of the sustainability equation [1]. By employing wind, solar, or hydropower for electric vehicles, public transit systems can further decrease their environmental impact. The example of electric buses in Knoxville demonstrates the viability of integrating renewable energy solutions, such as solar panels, in public transit systems [11]. This approach not only promotes ecological sustainability but also serves as a blueprint for other cities to follow [52].

In conclusion, analyzing the environmental impact of public transit systems and exploring sustainable solutions are crucial steps toward a greener future. By embracing electric vehicles, renewable energy sources, and supportive government policies, public transport systems can become more environmentally friendly, cost-effective, and efficient for users. The insights and discussions presented in this subsection aim to contribute to a deeper understanding of the challenges and opportunities that lie ahead in optimizing public transport systems while minimizing their ecological footprint. Consequently, this research strongly advocates for the adoption of innovative electric solutions and cautions against the use of outdated systems such as diesel or coal-charged transit.

1.3 Public Safety

A case for consequences related to public transit inefficiencies other than mere economic faults can be identified by looking no further than a case study of the KAT public transit system. Sprawling cities often lack the necessary public amenities such as sidewalks making cities very dangerous for those without cars [79, 16]. A very sad but pertinent example is that of Ben Kredich, a (mentally disabled) 23-year-old who depended on the routes to provide transportation to and from work, dinner, etc. Knoxville had been making budget cuts and the bus route that he normally used was suspended or reduced so that its convenience was diminished greatly for its users. Mr. Kredich was quoted at a town hall meeting discussing the suspension of multiple bus lines, "I don't want it to go away forever because I really have to catch on time and I want them to just drop me off at Kingston Pike because all the cars. I didn't want to get hit by the cars, which can be dangerous" [30]. This was a very ominous statement as not a year later, he was walking along the same bus route and was run down by a driver under the influence in the middle of the day on his way downtown to eat with his father [63]. This death was inadvertently influenced by inefficiency within Knoxville public transit. As public transit should not be taken away or reduced if it has any use. This can be considered a public right that must be offered by a municipality such as Knoxville [8].

In cities grappling with inadequate public amenities such as sidewalks, the consequential reduction or suspension of bus routes not only creates logistical challenges but also raises profound safety concerns, particularly for individuals without access to private transportation [79, 16]. The dearth of essential infrastructure, compounded by limitations in public transit options, results in a tangible infringement on an individual's fundamental right to move freely throughout a city. This curtailed mobility not only hinders access to vital services and opportunities but also engenders heightened levels of mental anguish among the city's population [33].

Moreover, the adverse impact extends beyond mere inconvenience, evolving into a significant societal concern. The restricted mobility arising from the lack of comprehensive public amenities contributes to a palpable sense of social inequity, disproportionately affecting vulnerable communities. Individuals who rely on public transportation as their primary means of mobility are particularly burdened by reduced bus routes, exacerbating existing disparities in access to essential services and employment opportunities.

This multifaceted challenge necessitates a comprehensive examination of urban planning and resource allocation to address the interconnected issues of infrastructure deficiencies and transportation limitations. Efforts to enhance public amenities, including sidewalks and robust public transit systems, become imperative not only for the practical facilitation of movement but also as a means to uphold the basic rights and well-being of urban dwellers. As cities strive for equitable and accessible urban landscapes, the enhancement of public amenities and transit infrastructure emerges as a cornerstone for fostering inclusive and resilient communities.

The heartbreaking incident highlighted above demonstrates the potentially life-threatening consequences associated with inefficiencies in public transit systems. The vulnerability of individuals, such as Mr. Kredich, emphasizes the critical role that reliable and accessible public transportation plays in ensuring the safety of urban residents [30, 63]. This example serves as a poignant reminder that public transit is more than just an economic consideration—it is a public right and a crucial aspect of urban life [8]. The challenges faced by the KAT system highlight the need for a comprehensive approach to address inefficiencies and enhance the overall effectiveness of public transit.

1.4 Social and Socioeconomic Inequalities in Public Transit

The adverse impact of public transit inefficiencies extends well beyond inconveniences and safety concerns, evolving into a significant societal challenge. The constrained mobility resulting from the lack of comprehensive public amenities contributes to a palpable sense of social inequity, disproportionately affecting vulnerable communities [33]. Statistically speaking, "Americans who are lower-income, black or Hispanic, immigrants or under 50 are especially likely to use public transportation regularly," as stated by [5]. These marginalized groups rely heavily on public transportation as their primary means of mobility and are particularly burdened by reduced bus routes, exacerbating existing disparities in access to essential services and employment opportunities [77].

These repercussions extend beyond mere marginalized logistical challenges, delving into profound societal implications, especially in cities grappling with inadequate public amenities [77]. The scarcity of essential infrastructure, coupled with limitations in public transit options, constitutes a tangible infringement on individuals' fundamental right to move freely throughout a city. This connection becomes notably evident when examining the impact of limited public amenities on underprivileged populations, particularly in the context of food deserts [95]. Food deserts are characterized by a lack of accessible and affordable sources of fresh, nutritious food, primarily affecting low-income communities [31]. In these areas, residents face significant challenges in obtaining healthy food options due to the spatial mismatch between their living spaces and grocery stores [31]. Public transportation plays a crucial role in mitigating this challenge, providing a lifeline for individuals in underprivileged communities to access essential resources, including grocery stores offering fresh produce and other nutritional necessities [10]. Therefore, the inadequacy of public transit options in these regions exacerbates the existing difficulties faced by residents in food deserts, further limiting their mobility and perpetuating disparities in access to vital resources [10]. This interconnectedness underscores the importance of addressing transportation infrastructure to create more equitable and accessible urban environments, particularly in areas impacted by food deserts.

In conclusion, this curtailed mobility not only obstructs access to vital services and opportunities but also intensifies levels of mental anguish among the city's population. Moreover, the adverse impact disproportionately affects vulnerable communities, amplifying existing social inequities. Individuals who predominantly rely on public transportation find themselves disproportionately burdened by reduced bus routes, heightening disparities in access to essential services and employment opportunities. Addressing these intertwined challenges requires a holistic approach, considering both transportation infrastructure and the accessibility of fundamental resources such as fresh and healthy food. As cities strive for equitable and accessible urban landscapes, the augmentation of public amenities and transit infrastructure emerges as a cornerstone for fostering inclusive and resilient communities.

This multifaceted challenge necessitates a comprehensive examination of urban planning and resource allocation to address the interconnected issues of infrastructure deficiencies and transportation limitations. Efforts to enhance public amenities and optimize public transit become imperative not only for the practical facilitation of movement but also as a means to uphold the basic rights and well-being of urban dwellers [81]. As cities strive for equitable and accessible urban landscapes, the enhancement of public amenities and transit infrastructure emerges as a cornerstone for fostering inclusive and resilient communities.

1.5 Conclusion of Impacts

The provision of high-quality public transportation, characterized by convenient, comfortable, and rapid service, stands as a catalyst for numerous positive impacts on public health and well-being. Efficient and reliable public transportation systems contribute significantly to the reduction of traffic crashes, creating safer urban environments for residents and commuters alike.

In conjunction with advanced transportation systems, transit-oriented development assumes a pivotal role in shaping healthier communities, aligning seamlessly with the overarching theme of "Uber Meets Bus: A Simulation Study of Public Ride-hailing Service." The promotion of walkable, mixed-use neighborhoods centered around transit stations not only fosters a sense of community but also encourages physical activity [9]. This emphasis on walkability contributes to increased physical fitness levels among residents, establishing a lifestyle that supports overall health. Moreover, the integration of transit-oriented development and high-quality public transportation not only enhances physical health but also positively influences mental health outcomes. The creation of well-designed, accessible urban spaces encourages social interactions, reduces feelings of isolation, and contributes to the overall well-being of the community [62]. The synergy between transit-oriented development, walkability, and efficient public transit systems highlights the potential for comprehensive urban planning to create vibrant, healthy, and interconnected communities.

The holistic benefits extend beyond safety and physical and mental health to encompass fundamental aspects of daily life. The combined approach facilitates improved access to essential healthcare and public services [9]. Residents in transit-oriented, well-connected communities are better positioned to meet their basic needs, fostering a foundation for long-term health and well-being [62].

In conclusion, the culmination of efficient public transportation and transit-oriented development not only enhances the physical and mental well-being of urban communities but also addresses the profound issue of financial stress, particularly for lower-income households [62]. By reducing reliance on personal vehicles, individuals and families experience increased affordability and financial stability, alleviating the burdens associated with car ownership. The high costs of purchasing, maintaining, and fueling personal vehicles often pose significant challenges, especially for those with limited financial means. The embrace of efficient public transportation systems offers a viable and cost-effective alternative, providing a comprehensive solution to the economic stress associated with car ownership [9]. This shift not only promotes financial equity but also contributes to the creation of a more sustainable, accessible, and resilient urban environment. Hence, the collaborative impacts of effective public transportation and transit-oriented development emphasize the diverse advantages that reach beyond transportation efficiency, molding cities into healthier, more interconnected, and economically equitable urban landscapes.

1.6 Background and Scope of Literature

A recognized response to address the transportation needs of the socioeconomically disadvantaged is the implementation of a paratransit system. Designed as an auxiliary service for individuals facing economic or physical challenges, paratransit aims to safeguard their access to public transportation [22]. Paratransit services are characterized as supplementary to conventional mass transit, deviating from fixed routes to cater to individual needs [88]. Extensive research has emanated from the realm of paratransit, often positioned as a supportive component to a broader transit network. However, this study diverges in focus, envisioning paratransit as an independent and robust system, aligning with the proposals articulated by Billheimer et al. [15].

Dial-a-Ride systems, recognized for their capacity to offer flexible and inclusive transit services, have garnered substantial attention in the literature [82]. This system employs two prevalent approaches: advanced reservation and a dynamic, uber-like ride-sharing system [48]. The advanced reservation model (static model) optimizes public transit efficiency and minimizes customer waiting times through proactive scheduling. Customers submit ride requests one day in advance, enabling the system to devise the most efficient routes based on transportation availability [82]. While this method adeptly diminishes waiting times and augments system efficiency in simulations, its efficacy is hindered by the capricious nature of customer demands and traffic patterns. Additionally, the requirement for riders to proactively schedule rides in advance imposes constraints on the flexibility of spontaneous trip planning [73]. The system's efficiency can also be hindered by instances of no-shows or late cancellations, introducing unpredictability into the scheduling process [73]. This structured framework may not seamlessly align with the dynamic and unpredictable nature of individuals' transportation needs. Consequently, there arises a crucial need to explore alternative strategies that can more effectively accommodate the spontaneous nature inherent in certain transportation scenarios. This consideration is essential for enhancing the adaptability and responsiveness of public transit systems to the real-time demands of passengers. As unpredictabilities, such as no-shows, pose challenges to the optimal functioning of scheduled services, investigating robust strategies to address and mitigate these issues becomes imperative for the overall efficiency of the public transit system [73].

The dynamic, real-time ride service, akin to an Uber model, offers customers the flexibility of on-demand rides, potentially optimizing key performance indicators of the transit system [40, 82]. This approach generates optimal routes dynamically as customers call in, providing a convenient and flexible system. While researchers have found solutions for both reservation and real-time ride-hailing scenarios through simulations [35], the optimal solution may not always be achievable due to the computational complexity associated with accommodating stochastic customer demands and traffic patterns.

Several scholars have conducted in-depth analyses, uncovering viable solutions for both reservation-based and real-time ride-hailing (uber-like)/(dynamic) scenarios through the application of sophisticated simulation methodologies [35]. Leveraging simulation approaches, researchers systematically examined the efficacy of each system, meticulously delineating their respective successes and drawbacks. This insightful investigation serves as a valuable foundation for probing the optimal solutions within the static reservation framework. The nuanced insights derived from these simulations offer a strategic vantage point, providing a comprehensive understanding of the strengths and limitations inherent in both reservation and real-time ride-hailing paradigms. As the simulation approach illuminates the comparative effectiveness of these systems, it lays the groundwork for a meticulous exploration of optimal strategies tailored to static reservation scenarios, enriching the discourse on the evolution and enhancement of public transit systems [39].

In addition to these models, a hybrid system is considered, combining traditional route services with on-demand helper buses. The limitations arising from the advanced scheduling (static) and dynamic approaches may curtail the system's responsiveness to real-time demands as well as advanced riders or lines potentially impeding its ability to cater to immediate and unplanned travel requirements which will happen in real-life [7]. In this hybrid model, main routes operate during peak times, while helper buses run continuously throughout the day. This approach aims to curtail costs while enhancing accessibility [25]. By operating during peak hours, main routes cater to high-demand periods which we are considering the static side, while the on-demand helper buses provide continuous service, offering a balance between efficiency and accessibility. The exploration of these various models, along with a nuanced comparison, is essential to understanding their respective strengths and weaknesses, contributing to the ongoing discourse in transportation optimization [78].

The optimization of pickup and dispersal procedures for uber-like vans (paratransit) has attracted considerable research interest. The initial consideration has been the implementation of the First-in-First-out (FIFO) or first-come, first-serve approach [34]. The approach employed in this method relies on a basic queue system where customers make ride requests and are subsequently placed in a queue, with the first in line receiving the next available ride to their desired destination. However, this method may not be the most optimal one, particularly when multiple customers necessitate pickups in the same vicinity or require transportation to similar locations. Furthermore, the FIFO system may result in the van returning to a previous pickup location, leading to reduced efficiency [21]. Therefore, to optimize the process, it is necessary to use an algorithm that determines the most optimal routes for multiple pickups and multiple deliveries while still maintaining an acceptable level of efficiency. However, this vehicle routing optimization process is stochastic and can be considered NP-Hard with large data sets [58]. Nonetheless, Al-Abbasi et al. [2] employed deep learning techniques to improve the performance of the models, providing a promising approach to addressing this complex NP-Hard problem.

Agent-Based Modeling (ABM) has emerged as a pivotal methodology in public transportation modeling, offering an insightful lens through which to understand and optimize transit systems. ABM simulates the actions and interactions of autonomous agents, such as passengers, drivers, and vehicles, to assess their collective impact on the system. Each agent operates based on a set of rules and behaviors, which can be influenced by real-time data, environmental factors, and interactions with other agents [57].

ABM is particularly adept at capturing the heterogeneity of behaviors and preferences among different user groups [37]. This allows for the modeling of complex phenomena such as route choice behavior, ride-sharing dynamics, and the spread of information among passengers. By simulating individual decision-making processes and interactions, ABM provides a granular understanding of how localized actions can scale up to influence overall system performance. This is a key to the reasoning behind the use of agent-based modeling [60]. This makes it an invaluable tool for designing and testing new policies, optimizing service schedules, and improving customer satisfaction in dynamic and unpredictable transit environments.

Digital twins, closely related to ABM, represent a cutting-edge approach to public transportation modeling. A digital twin is a virtual replica of a physical system, updated in real-time using data from sensors, IoT devices, and other sources [87]. In the context of public transportation, a digital twin can replicate an entire transit network, including vehicles, routes, stations, and passenger flows. This virtual model continuously evolves with the real system, providing a live, interactive platform for analysis and optimization. Digital twins facilitate scenario testing and what-if analysis, allowing transit agencies to simulate the impact of potential changes before implementing them. This helps in making informed decisions, optimizing resource allocation, and improving service quality. Lastly, digital twins support the development of adaptive and resilient transit systems by providing a comprehensive understanding of system dynamics and enabling proactive responses to emerging challenges [83].

What distinguishes this study is the innovative use of US Census data to predict demand in public transportation modeling, which has not been done before. US Census data provides a comprehensive and granular understanding of population distribution, socioeconomic characteristics, commuting patterns, and travel behaviors [4]. By leveraging this data, our simulation better accounts for the variability and dynamics of transit demand, leading to more informed decision-making and improved service planning. This approach enhances the adaptability and responsiveness of public transit systems to real-time demands and demographic changes, ultimately contributing to the optimization of transportation networks.

1.7 Overview of Problems

In this thesis, we embark on a dual exploration, commencing with an examination of the Dial-A-Ride Problem (DARP) and its intricate subproblems within transportation optimization.

Addressing the static versus dynamic nature of transportation systems, we unravel the computational challenges associated with predetermined routes and stochastic customer traffic. Concurrently, we delve into related optimization complexities, encompassing the Pick-Up and Delivery Vehicle Routing Problem (PDVRP), the Vehicle Routing Problem with Time Windows (VRPTW), and the renowned Traveling Salesman Problem (TSP). This scrutiny sets the stage for a deeper investigation into the NP-hard nature of these challenges, revealing their exponential computational complexity. The subsequent section navigates the computational intricacies through an exploration of metaheuristic strategies, offering invaluable tools to address NP-hard challenges in transportation optimization. From Genetic Algorithms to Particle Swarm Optimization, we delve into a nuanced examination of these methodologies, each serving as a sophisticated instrument for researchers to navigate the intricate landscape of optimization problems in transportation.

1.7.1 DARP and Combinatorial Optimization Challenges in Transportation

The Dial-A-Ride Problem (DARP) stands as a pivotal subject in the realm of transportation optimization, captivating the attention of researchers seeking to enhance the efficiency of contemporary transit systems [82]. This intricate problem unfolds into a tapestry of subproblems, each intricately woven into the fabric of transportation literature. One such subproblem that merits in-depth exploration is the Static vs. Dynamic Dial-a-Ride Problem.

In delineating these two paradigms, a static transportation system adheres to an unchanging set of bus routes, maintaining a predetermined path regardless of customer traffic variations [25]. This stability, while simplifying the optimization process, hinges on the premise that travel demand remains constant and impervious to temporal fluctuations. The predetermined nature of static systems renders them relatively more straightforward to optimize, as the fixed routes facilitate efficient resource allocation [90].

Conversely, the dynamic counterpart introduces stochastic elements, creating a more fluid and adaptive transportation system. Dynamic systems acknowledge the inherent variability in customer traffic, acknowledging that travel demand is subject to change over time [25].

While dynamic systems offer flexibility in responding to real-time variations, their stochastic nature presents a computational challenge. The task of finding the optimal solution becomes inherently more complex as it involves navigating the unpredictable dynamics of customer demand, introducing a layer of computational intricacy [25].

This exploration of the Static vs. Dynamic Dial-a-Ride Problem thus illuminates the contrasting facets of transportation optimization. The dichotomy between static and dynamic systems underscores the trade-off between simplicity and adaptability [91], as researchers grapple with the challenge of finding optimal solutions amidst the varying landscapes of customer demand. As we traverse this nuanced terrain, insights derived from these studies contribute not only to the theoretical understanding of DARP but also offer practical implications for refining and advancing contemporary transportation systems.

Beyond the focal point of the Dial-A-Ride Problem (DARP) lies a rich tapestry of related optimization challenges that have garnered considerable attention within the field of transportation research. One such intricate challenge is the Pick-Up and Delivery Vehicle Routing Problem (PDVRP), an exploration that delves into the complexities of efficiently transporting goods between various locations [75]. This variant of DARP involves a fleet of vehicles tasked with the dual mission of picking up and delivering goods while striving to minimize the total distance traveled [75]. As a dynamic extension of the original problem, PDVRP not only addresses the optimization of routes but also emphasizes the importance of resource allocation in minimizing the overall transportation costs associated with goods delivery.

Expanding further into this realm of transportation optimization challenges, the Vehicle Routing Problem with Time Windows (VRPTW) emerges as a critical area of study [71]. This problem extends the conceptual boundaries of PDVRP [75] by introducing temporal constraints into the equation. In VRPTW, each customer is assigned a specific time window during which deliveries and pick-ups must occur [71]. This temporal dimension adds a layer of complexity to the optimization task, as the routing algorithm must not only consider spatial proximity but also adhere to stringent time constraints. The delicate balance between spatial and temporal considerations becomes pivotal in crafting solutions that are not only efficient in terms of distance but also temporally aligned with the constraints of real-world scenarios.

As researchers navigate the multifaceted landscape of these related problems, their studies contribute not only to the theoretical understanding of transportation optimization but also offer practical insights for refining and advancing real-world logistics systems. The juxtaposition of DARP with PDVRP and VRPTW showcases the versatility and adaptability of optimization models, each tailored to address specific nuances inherent in diverse transportation scenarios. Through these explorations, scholars aim not only to uncover theoretical intricacies but also to provide actionable solutions that resonate with the dynamic challenges of contemporary transportation logistics.

The Traveling Salesman Problem (TSP), a classic conundrum in combinatorial optimization [45], remains a focal point of extensive research within the realm of transportation optimization. This problem entails the quest for the most efficient route that visits all specified targets and subsequently returns to the starting point. Renowned for its computational complexity, the TSP is classified as NP-hard, signifying an escalation of computational infeasibility with an increasing number of destinations [51]. As scholars grapple with the intricacies of this challenging problem, further exploration extends beyond the conventional TSP framework.

Within the broader spectrum of Dial-A-Ride Problem (DARP) research, additional variants and extensions emerge, amplifying the complexity of optimization tasks. Notably, the Multiple Traveling Salesman Problem (MTSP) [23] emerges as a significant focal point. This extension introduces the concept of multiple salesmen, each tasked with devising an optimal route to visit assigned targets exactly once, minimizing the collective distance traveled [49]. The practical applications of MTSP are diverse, ranging from mail delivery and garbage collection to vehicle routing, rendering it a critical area of exploration in contemporary transportation optimization research [23].

Furthermore, the Time-Dependent Traveling Salesman Problem (TD-TSP) introduces a realistic dimension by considering the dynamic nature of traffic flow [3]. This temporal aspect acknowledges that travel times between destinations can vary based on the time of day or day of the week, aligning more closely with real-world scenarios [65]. As the TD-TSP aligns with the challenges posed by fluctuating traffic conditions, its exploration becomes imperative in enhancing the practicality and applicability of optimization solutions within the broader context of transportation [3].

In summary, the expansive exploration of TSP and its variants [47] within the DARP domain showcases the evolving landscape of transportation optimization research. Scholars navigate the intricacies of these NP-hard problems, leveraging diverse methodologies and frameworks to address the escalating computational challenges. As we delve into these nuanced problem spaces, the insights garnered contribute not only to theoretical advancements but also offer practical implications for optimizing real-world transportation systems [47].

The intricacies of combinatorial optimization problems [72], exemplified by the Dial-A-Ride Problem (DARP) [26] alongside the Pick-Up and Delivery Vehicle Routing Problem (PDVRP) [14] and the Vehicle Routing Problem with Time Windows (VRPTW) [59], represent a formidable class of computational challenges. Specifically, these problems fall under the category of NP-hard, denoting a computational complexity that escalates exponentially with the size of the input [41].

The NP-hard nature of these problems implies a fundamental computational limitation: no known polynomial-time algorithm can solve them exactly for arbitrary problem sizes [44]. In the context of transportation optimization, where the number of variables and constraints can be vast, the absence of a polynomial-time solution introduces significant computational hurdles [41]. As the size of the problem instances increases, the computational demands escalate at a pace that renders exact solutions impractical, especially for real-world scenarios [41].

The exploration of the Dial-A-Ride Problem (DARP), along with its related optimization challenges such as the Pick-Up and Delivery Vehicle Routing Problem (PDVRP) and the Vehicle Routing Problem with Time Windows (VRPTW), underscores the complexity and computational intensity inherent in transportation optimization. These NP-hard problems reveal the intricate balance between efficiency, adaptability, and real-world applicability. The classical Traveling Salesman Problem (TSP) and its variants further highlight the diverse methodologies required to address the escalating computational challenges.

Relating these mathematical models to a bus and Uber simulation, it becomes evident why their theoretical foundations are pivotal. In simulation research, understanding the optimization frameworks allows for the creation of more realistic and efficient models. For instance, the static vs. dynamic paradigms in DARP illustrate the necessity of adapting to real-time variations in demand, a crucial aspect for accurately simulating urban transit systems. The integration of these optimization principles enables the simulation to account for the variability and unpredictability of passenger demand, ensuring more robust and applicable outcomes.

By leveraging the insights from these combinatorial optimization problems, the bus and Uber simulation can better address the trade-offs between fixed schedules and dynamic routing. This approach ensures that the simulation not only mirrors the complexities of real-world scenarios but also provides practical solutions for enhancing the efficiency and reliability of contemporary transit systems. Thus, the exploration of these mathematical models forms the bedrock upon which simulation research can build more accurate and effective transportation systems, ultimately contributing to the advancement of public transportation modeling.

1.7.2 Heuristics: Balancing Pragmatism and Computational Efficiency

Heuristics, as computational strategies, play a pivotal role in addressing the intricacies of NP-hard challenges, particularly within the domain of transportation optimization [36]. These approaches prioritize practicality and computational efficiency, offering a valuable solution to complex problems where obtaining a quick and reasonably effective result is imperative [68]. In the context of transportation optimization, heuristics are designed to rapidly provide approximate solutions, catering to the real-time decision-making demands of dynamic systems [56, 46]. This pragmatic advantage, however, comes with a trade-off. Heuristics do not guarantee the attainment of globally optimal outcomes, acknowledging the compromise made for the sake of expeditious solution derivation [80].

Within the realm of transportation optimization, several heuristic methodologies prove instrumental in addressing computational challenges efficiently. The Nearest Neighbor Algorithm, as proposed by Kizilatecs *et al.* [55], is a widely employed strategy that prioritizes proximity in route planning. This algorithm operates by iteratively selecting the closest available destination at each step of the route construction process. Rapidly constructing a solution, the Nearest Neighbor Algorithm proves effective in scenarios where real-time decision-making is crucial [84]. However, it should be noted that the approach, while expedient, does not guarantee globally optimal solutions due to its reliance on local proximity metrics [55].

Insertion Heuristics presents another valuable approach to transportation optimization. This methodology dynamically inserts locations into an existing route, intending to optimize the overall path [19]. Unlike the Nearest Neighbor Algorithm, Insertion Heuristics balance computational efficiency with the need for iterative refinement. This involves strategically placing locations into the existing route, considering their impact on the overall path quality [29]. The iterative refinement process contributes to solution precision, making Insertion Heuristics particularly suitable for scenarios where an initial solution can be progressively enhanced. The adaptability of this approach allows it to handle complex optimization challenges while maintaining computational efficiency [19].

Additionally, the Sweep Algorithm, as introduced by Nurcahyo [70], further enriches the heuristic toolkit in transportation optimization. This algorithm systematically divides the solution space into sectors and constructs routes by methodically ”sweeping” through them. Particularly adept at handling large-scale problems, the Sweep Algorithm strategically manages the exploration of the solution space, providing an efficient balance between computational speed and solution quality [69]. The systematic approach of the Sweep Algorithm makes it a valuable asset in scenarios where exhaustive searches would be computationally prohibitive.

The pragmatic advantages of employing heuristics in transportation optimization are multifold. First, heuristics enable real-time decision-making, crucial in dynamic transportation systems, allowing immediate responses to changing conditions and contributing to operational efficiency. Second, the rapid derivation of approximate solutions meets time-sensitive operational demands [38]. Heuristics efficiently navigate large solution spaces, ensuring timely outcomes.

In conclusion, the employment of heuristics in transportation optimization significantly enhances the practical application of theoretical models in real-world scenarios. When applied to a bus and Uber simulation, these heuristic strategies facilitate the development of dynamic and adaptive transit systems. By integrating heuristic methods, simulations can swiftly respond to changing passenger demands and optimize routes in real-time, thus bridging the gap between theoretical optimization and practical implementation in public transportation modeling. This ensures that the simulation not only replicates real-world conditions accurately but also provides actionable solutions for improving the efficiency and reliability of contemporary transit systems.

1.7.3 Metaheuristics: Informed Exploration and Iterative Improvement

Metaheuristics represent a sophisticated and advanced class of algorithms that elevate the optimization process to a new level of efficiency and adaptability within NP-hard problems [36]. This section will provide a nuanced exploration of metaheuristic approaches, emphasizing their role in guiding the search for optimal solutions through informed exploration of solution spaces.

Metaheuristics stands out by incorporating iterative improvement strategies, allowing them to adapt and refine solutions over multiple iterations. Unlike heuristics, metaheuristics undertake a more deliberate and informed exploration of the solution space. This intentional approach enhances their ability to navigate complex problem landscapes and overcome the limitations of traditional heuristic methods [28].

The following will delve into specific metaheuristic methodologies, each with its unique characteristics and strengths. Genetic Algorithms (GAs) simulate biological evolution [74], Simulated Annealing (SA) introduces controlled randomness for global convergence [94], Tabu Search (TS) employs a memory structure to prevent revisitation and stagnation

[94], Ant Colony Optimization (ACO) leverages collective intelligence [92], Particle Swarm Optimization (PSO) emulates social behavior [89], and Iterated Local Search (ILS) integrates perturbation for iterative refinement [64].

Genetic Algorithms, inspired by biological evolution [74], operate by maintaining a population of potential solutions and subjecting them to evolutionary processes such as crossover and mutation. This emulation of natural selection enables GAs to navigate complex solution spaces effectively. The strength lies in their ability to explore diverse regions, but the downside includes potential premature convergence to suboptimal solutions [53].

Simulated Annealing, introducing controlled randomness for global convergence [94], is particularly valuable in exploring diverse solution regions. By accepting probabilistically worse solutions during the search, SA can escape local optima. However, its sensitivity to optimal parameters and the potential for slow convergence are notable considerations [32].

Tabu Search, employing a memory structure to prevent revisitation and stagnation [94], strategically avoids previously explored solutions. This deliberate avoidance prevents stagnation in local optima, encouraging exploration of the broader solution landscape [12]. On the downside, defining effective tabu rules can be challenging, and the search may become too conservative.

Ant Colony Optimization, leveraging collective intelligence [92], models ant foraging behavior using pheromone trails to guide the algorithm towards promising regions of the solution space. Particularly effective in routing and scheduling problems, ACO reflects adaptability and efficiency derived from collective intelligence. However, ACO may struggle in dynamic environments due to its reliance on static trails simulated with ant movement [17].

Particle Swarm Optimization, emulating social behavior [89], maintains a swarm of particles dynamically adjusting their positions based on individual and collective knowledge. Striking a balance between exploration and exploitation, PSO enhances adaptability in diverse solution landscapes. However, PSO can converge prematurely to suboptimal solutions in certain scenarios [66].

Iterated Local Search, integrating local search with perturbation for iterative refinement [64], progressively converges towards improved and more globally optimal outcomes. The iterative refinement process contributes to the precision of optimization results. However, ILS might be computationally expensive due to repeated local searches, and its performance can be sensitive to parameter tuning [76].

In summary, each metaheuristic approach brings its unique strengths to the table, addressing specific aspects of optimization challenges. However, understanding their potential downsides is crucial for informed application and effective integration into transportation optimization scenarios. Concurrently, comprehending the structural nuances and constraints of the transportation optimization problem becomes paramount in selecting an appropriate metaheuristic approach. This section provides an in-depth analysis of metaheuristic strategies, highlighting their sophistication and effectiveness in addressing the computational challenges associated with NP-hard optimization problems. By doing so, the study contributes not only to the advancement of transportation system efficiency but also enriches the broader field of optimization research.

Expanding the research landscape, recent advancements have seen an increasing reliance on artificial intelligence and machine learning techniques to address the complexities of transportation optimization problems. Integrating these technologies holds the promise of enhancing the precision and adaptability of solutions in dynamic and real-world scenarios.

By incorporating these advanced metaheuristic methods into a bus and Uber simulation, the optimization process can significantly benefit. The ability of metaheuristics to adapt and refine solutions over multiple iterations allows for more accurate and efficient modeling of complex transportation systems. This leads to simulations that not only closely mirror real-world conditions but also offer practical solutions for improving transit system efficiency and reliability. Thus, the exploration of metaheuristic strategies forms a crucial foundation for developing advanced and realistic simulations in public transportation modeling.

Chapter 2

Solution Methods

To enable a meticulous evaluation of the diverse proposed modes of transportation, it was vital to adopt a methodology that could provide a comprehensive analysis of system outcomes. As a result, the determination was made that simulating the different transportation scenarios would offer the most insightful perspective. The subsequent sections of this study are dedicated to the clarity of the simulation's creation and implementation, valuing the intricacies of the various agents involved and defining and describing their dynamic interactions.

The simulation design is underpinned by a rigorous exploration of agents' behavior, elucidated through the systematic integration of statecharts, analytical insights, and algorithmic frameworks. Statecharts serve as a visual representation of the dynamic states and transitions within the simulation, offering a structured depiction of agent behaviors. Analytical insights contribute an additional layer of depth to the examination, providing a theoretical framework for understanding the observed phenomena and optimizing system performance. Furthermore, algorithms play a pivotal role in orchestrating the agents' actions, introducing a level of computational precision that enhances the simulation's accuracy and reliability.

This methodological approach not only facilitates a nuanced examination of the transportation scenarios but also ensures a robust foundation for drawing meaningful conclusions. The utilization of state-of-the-art tools, such as AnyLogic aligns with the advanced standards expected at the master's level, emphasizing both the theoretical and practical dimensions of the simulation methodology. The ensuing sections will expound upon these elements, delving into the intricate details of the simulation process and its implications for the broader understanding of proposed transportation modes.

2.1 Bus Simulation

The selection of simulation as the methodology for assessing Uber and bus route scenarios is grounded in its capacity to provide a holistic and dynamic representation of complex transportation systems. Simulation serves as an invaluable tool for modeling the intricate interactions between various components, including vehicles, passengers, and infrastructure, within a dynamic urban environment. In the context of Uber and bus route simulations, this approach enables the exploration of real-world scenarios under diverse conditions, allowing for a nuanced examination of how these modes of transportation operate and interact within the urban landscape.

The usefulness of simulation lies in its ability to capture the variability and unpredictability inherent in transportation systems. For Uber, the simulation can simulate ride requests, driver behaviors, and response times, offering insights into the system's efficiency, reliability, and overall performance. In the case of bus routes, the simulation can model factors such as passenger boarding and alighting patterns, traffic conditions, and route deviations, providing a comprehensive understanding of the operational dynamics.

Additionally, simulation allows for scenario testing and sensitivity analysis, providing a platform to evaluate the impact of different variables and conditions on system outcomes. This enables researchers and policymakers to explore the resilience and adaptability of Uber and bus route systems to varying demands, disruptions, and environmental factors.

By choosing simulation, this study aims to bridge the gap between theoretical insights and practical implications, offering a robust and versatile framework for decision-making in urban transportation planning. The simulation methodology aligns with the complexity of modern transportation systems, allowing for a nuanced evaluation of Uber and bus route scenarios and fostering a deeper understanding of their individual and collective contributions to urban mobility.

The bus simulation model, meticulously crafted within the framework of AnyLogic, embodies a comprehensive representation of the intricate behaviors and interactions inherent in a bus transit system. Developed under established standards for public transit systems [86], this model is designed to accommodate customization, thereby aligning with the specific objectives and goals of the simulation. Rooted in the sophisticated capabilities of AnyLogic, the bus simulation model serves as a dynamic platform for analyzing and clearing up the multifaceted dynamics of bus routes. Its adaptability and adherence to industry standards underscore its utility as an advanced tool for exploring the nuances of urban transportation systems, contributing to a refined understanding of the operational intricacies of both bus and Uber transportation modes.

2.1.1 Agents

The simulation of the bus system aims to replicate a real-life bus network. Consequently, the agents selected for the simulation include Main, Bus, Rider, Route, Tract, and Place of Interest (POI). The interactions between these agents reflect the dynamics of a typical bus system. This section will highlight the key functions, events, variables, and parameters that contribute to the system's value. Rather than delving into the intricate details of each component, we will provide a broad overview of the most important aspects.

The main agent is where the situation is set. See figure 2.1 for bus main and figure 2.2 for Uber main. It contains a GIS coordinate map focused on the parts of the city that are to be simulated. It contains some basic parameters that will be defined in the Experiments section. Within the GIS map is another collection of Tract agents. This data is from the U.S. Census Bureau and refers to demographic and socioeconomic information collected and reported at the level of census tracts. Census tracts are small geographic areas defined by the U.S. Census Bureau to gather and present detailed statistical data. These tracts are designed to be relatively homogeneous in terms of population characteristics, economic status, and living conditions [24].

Within main two important events are housed. The first event is add bus which checks every five minutes to see if another bus should be added based off the total busses to be added to the system. The second is an event called riderMovement which initializes the rider

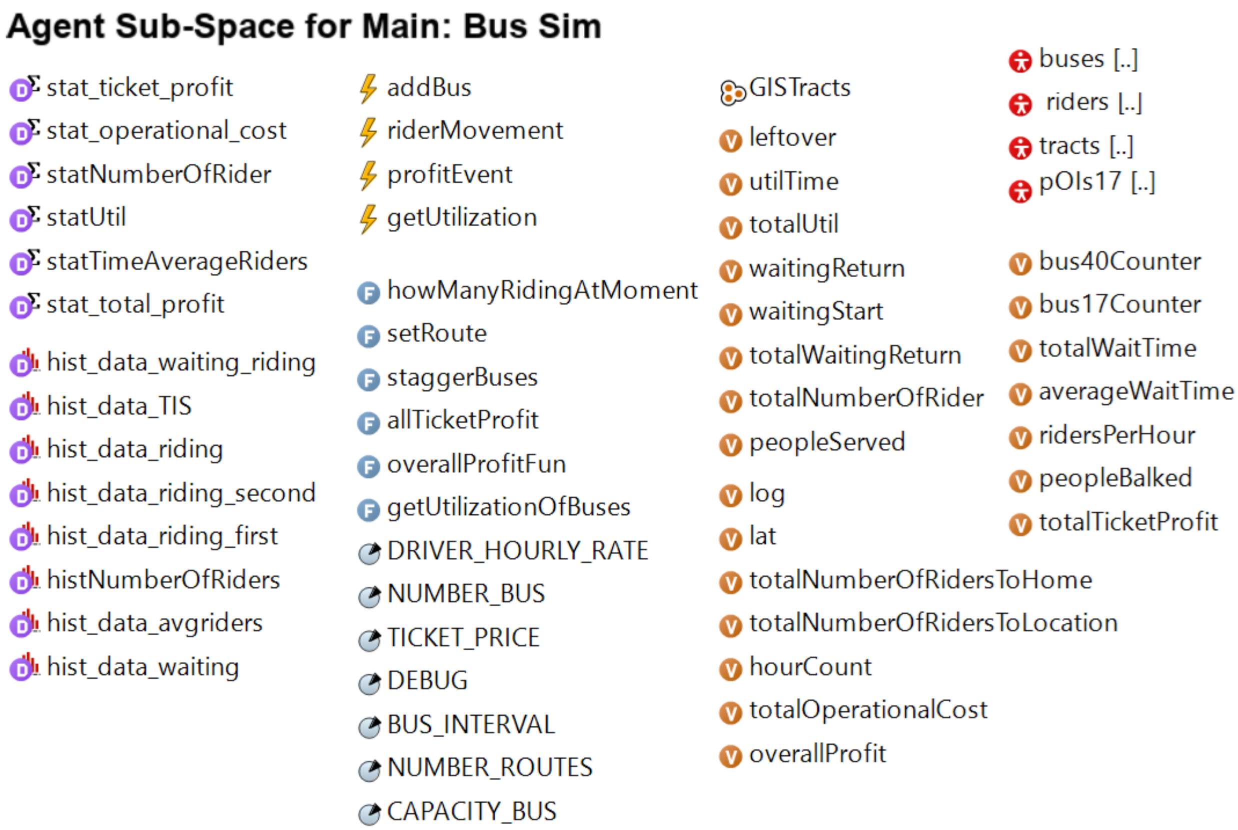

Figure 2.1: Main Agent: Sub-Space (Bus Sim)

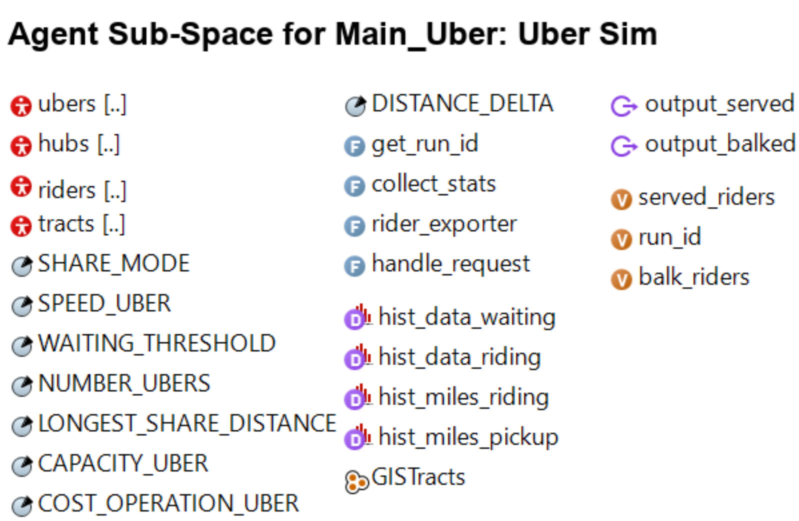

Figure 2.2: Main Agent: Sub-Space (Uber Sim)

to have a starting POI so that they can start their movement to that location. Other events cyclically pull stats, update tables, and enact functions.

In conjunction with managing events, the primary module orchestrates multiple functions designed to address distinct aspects of the simulation. The initial function, 'setRoute,' serves the purpose of determining the requisite number of routes upon initialization, predicated on the parameter denoted as 'NUMBER_ROUTES.' Subsequently, this function proceeds to establish these routes within the GIS map to facilitate simulation. Following this, a function is implemented to tactically stagger the deployment of buses. This operational procedure ensures that buses are incrementally introduced into the system only if both the route count and bus capacity fall below predefined thresholds ('NUMBER_ROUTES' and 'NUMBER_BUS,' respectively). This meticulous approach is aimed at guaranteeing an adequate fleet allocation across multiple routes.

Furthermore, the simulation includes a crucial financial analysis component, utilizing functions such as 'allTicketProfit' and 'allOperationalCost.' The 'allTicketProfit' function calculates the total profit generated by the system, while the 'allOperationalCost' function computes the overall operational expenses incurred. These functions are essential for evaluating the fiscal viability and sustainability of the simulated transportation network. They provide insights into potential adoption rates for municipalities, helping to determine if the benefits of reduced wait times and balking outweigh the costs of adding additional buses.

Finally, the culmination of these analytical processes culminates in the formulation of the 'overallProfitFun' function. Serving as an amalgamation of preceding financial assessments, this function provides a concise yet comprehensive evaluation of the system's overall profitability. By synthesizing revenue generation and operational costs, it furnishes stakeholders with valuable insights into the financial performance and efficacy of the simulated transportation system. To see the variables used in the above functions, please refer tofigure 2.1.

The definition of the bus agent required careful consideration of several fundamental parameters and variables to accurately model its operations within the simulation. Firstly, the bus operation schedule mirrors the scheduled hours of the Sutherland route, spanning

Table 2.1: Main Variables

Variable	**Type**	**Short Description**
totalWaitingReturn	Int	Sum of riders waiting at stop to return home.
totalOnBus	Int	Sum of riders currently riding bus.
peopleServed	Int	Total riders picked up and returned home.
log	Double	Original longitudinal coordinate for the rider to start in its assigned tract.
Lat	Double	Original latitudinal coordinate for the rider to start in its assigned tract.
waiting	Int	Number of riders waiting for rides.
totalNumberofRiders	Int	Total number of riders in system.
hourCount	Int	Total hours of all bus operations.
bus40Counter	Int	Variable used to add route 40.
bus17Counter	Int	Variable used to add route 17.
totalWaitTime	Double	Sum of all wait time experienced by a rider.
averageWaitTime	Double	Average time spent waiting by each rider in the system.
ridersPerHour	Double	Sets amount of riders per hour to be introduced to the system.
peopleBalked	Int	Total number of riders to balk from a bus stop.
totalTicketProfit	Double	Total dollar value brought in by the ticket sales to ride bus.
totalOperationalCost	Double	Total dollar value paid out to drivers for their work.
overallProfit	Double	Ticket sales minus operational cost to get overall profit.

Table 2.2: Main Parameters

Parameter	**Type**	**Short Description**
DEBUG	Boolean	Parameter used for debug testing to hide parts of code from the compiler.
BUS_INTERVAL	Int	Time between the release of busses.
NUMBER_ROUTES	INT	Total routes to be introduced to the simulation.
CAPACITY_BUS	Int	Max allowable riders to be on bus at anytime.
NUMBER_BUS	Int	Number of busses to be released to the system at specific intervals.
TICKET_PRICE	Double	Price of the ticket to be simulated with.

from 5:30 AM to 9:30 PM on weekdays, with adjusted times for weekends. Each bus agent is assigned a capacity of 49 passengers, based on standard capacity signage observed on KAT buses, alongside identification of the specific route to which the bus belongs. Additionally, a parameter is designated for the driver's hourly rate, set at $20/hr.

The variables for the bus agent encompass a range of crucial aspects and stats seen in figure 2.3 and in table 2.1. These include the number of riders aboard, indicating bus utilization and ensuring adherence to capacity limits, and a status/direction indicator for whether the bus is en route back to the depot. Further variables track the current and starting Points of Interest (POIs), facilitating route management and ensuring accurate routing decisions. Additionally, variables capture total ridership count, operational hours, operational cost per bus, and profit per bus, offering insights into operational efficiency and financial performance.

Of particular significance is the management of bus directional movement within the simulation. To accommodate unidirectional stops lacking corresponding stops for the opposite direction, a variable designates specific POIs to be exclusively serviced when the bus is returning to the depot. The current POI denotes the bus's present stop, while the start POI indicates its initial departure point, aiding in route tracking and management.

An essential function within the bus agent is 'getStartPOI,' which intelligently selects the starting POI based on the day of the week. This function plays a pivotal role in orchestrating route commencement, ensuring efficient deployment from either central hubs or nearby POIs. Subsequently, the 'busCost' function aggregates operational expenses, providing valuable insights for budgetary considerations and financial planning.

Lastly, the 'busDirection' function is instrumental in configuring bus directionality and color scheme based on its origin, enhancing route identification and operational clarity. This customization optimizes route management and contributes to the overall efficiency of the transit system.

In configuring parameters for the Rider agent, a set of crucial variables has been defined to govern its behavior within the simulation. These parameters encompass the agent's initial Point of Interest (POI), destination POI, ride-back start and destination, returning status, ride time, on-bus indicator, the specific bus it is on, nearest POI, stop presence, the number

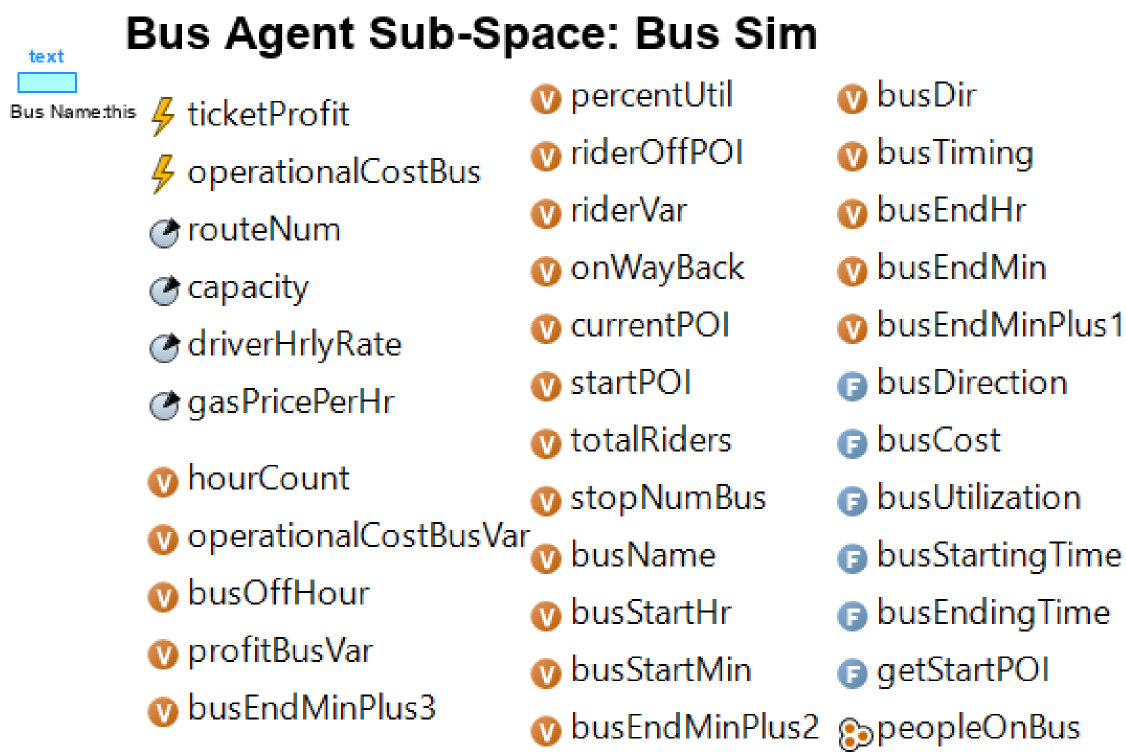

Figure 2.3: Bus Agent: Sub-Space (Bus Sim)

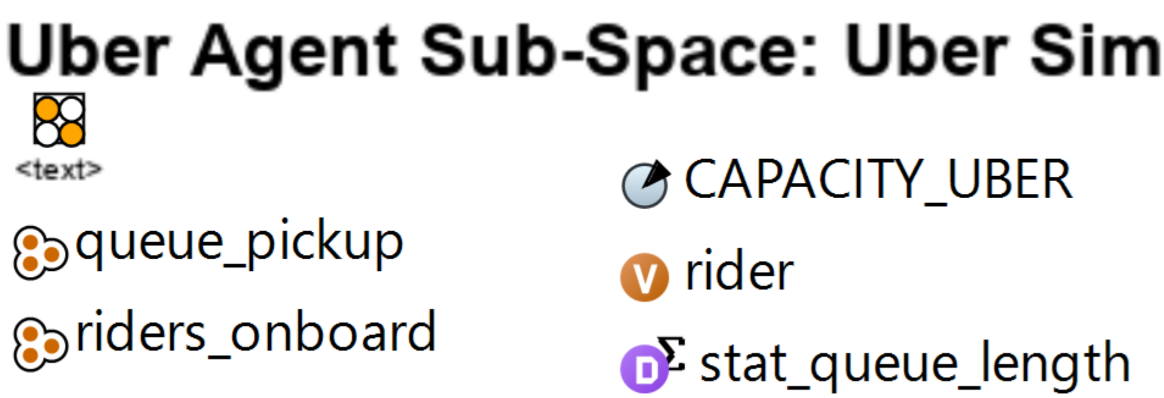

Figure 2.4: Uber Agent: Sub-Space (Uber Sim)

Algorithm 1 Bus Behavior

```
peopleOnBus ← []
riders ← 0
stop ← depot.nextStop
while operating do
    moveTo(stop)
    peopleToGetOff ← filter(peopleOnBus,
            e → e.onBus and e.destination.equals(stop))
    for all p in peopleToGetOff do
        remove p from peopleOnBus
        remove p from main.people
        p.onBus ← FALSE
        riders ← riders − 1
    end for
    peopleToGetOn ← peopleAtStop
    for all p in peopleToGetOn do
        if riders < capacityOfBus then
            remove p from peopleAtStop
            add p to peopleOnBus
            p.onBus ← TRUE
            riders ← riders + 1
        end if
    end for
    stop ← stop.nextStop
end while
```

Table 2.3: Bus Variables

Variable	Type	Short Description
riderVar	Int	Gives riders on bus.
onWayBack	Boolean	Shows if a bus if heading away from bus hub or back toward it.
currentPOI	POI	Is the current POI that the bus is stopped at.
startPOI	POI	define which stop to start at. Depends on day of week.
totalRiders	Double	Total Riders to get on bus.
hourCount	Double	Total hours all of the buses operate.
operationalCost	Double	Cost per hour to operate an individual bus.
profitBusVar	Double	Total money brought in by the public transit system.
stopNumBus	Int	The Index of the bus stops, which we use as a name.
busDir	Boolean	Sets bus direction based on day to in or out based on its daily schedule.

Table 2.4: Bus Parameters

Parameter	Type	Short Description
routeNum	Int	Naming convention of the route.
capacity	Double	Total number of riders allowed on bus.
driverHrlyRate	Double	The cost per hour of a driver.

of stops to wait, threshold wait time, initial start coordinates (x and y GIS), and the assigned route associated with the Person agent. The initial position is randomly assigned within a tract, ensuring proximity to stops along the designated Sutherland route to optimize the utilization of the bus system.

For realism, riders are intermittently released from the bus at random intervals, simulating the stochastic nature of ridership. To emulate natural variability, riders may occasionally stay on board beyond their intended ride time. The maximum riding time is defined as a triangular distribution ranging from 25 to 40 minutes, with an average of 30 minutes—reflecting the average duration of half the bus route. This approach considers the likelihood of passengers continuing beyond their destination, reinforcing the simulation's fidelity to real-world scenarios.

The release of riders at random Points of Interest (POIs), contingent on the ride time, ensures a dynamic and realistic distribution of destinations. This comes into effect on the rider startup. At startup, a rider's rideBackDestination, rideBackStart, and destination are all initialized to a random POI. We have to do this to counteract the Null Pointer Error. They, however, will be altered when a rider gets off and sets its new destination. The Algorithm to allow riders to get off the bus is below:

The provided algorithm serves a crucial role in ensuring that riders maintain a realistic duration aboard the bus, thus averting premature exits. This methodology takes into account common rider behavior, striving to replicate real-world scenarios where passengers typically remain on board for a reasonable period before disembarking. By establishing a threshold for the number of stops a rider encounters before contemplating departure, the algorithm significantly enriches the authenticity of simulated passenger actions.

Upon disembarking from the ride-hailing service, the algorithm employed not only determines the rider's destination but also incorporates the intricacies of ride-back considerations. This advanced functionality integrates simulated waiting periods, reflecting the intervals typically allocated for personal errands or other engagements. Through a meticulously crafted simulation, the algorithm replicates the temporal dynamics of real-world scenarios, employing a Triangular distribution model where the shortest waiting time is 30 minutes, the average is 60 minutes, and the longest is 160 minutes. Once the designated waiting

Algorithm 2 Set Rider's Destination and Determine When to Get Off

Initialize random number generator: **Random rando = new Random();**
Generate a random number between 10 and 20:
int randomNumo = rando.nextInt((20 - 10) + 1) + 10;
Initialize another random number generator: **Random rand = new Random();**
Generate another random number between 10 and 20: **int randomNum = rand.nextInt((20 - 10) + 1) + 10;**
for each rider r in *peopleOnBus* **do**
    Increment the number of stops the rider has been on: **r.stopsOnBus++;**
    if $r.stopsOnBus \geq randomNum$ **then**
        Set the rider's destination to k: **r.destination = k;**
    end if
end for

period elapses, the algorithm orchestrates the return journey to the original destination. However, a critical refinement emerges in cases where the original destination lacks bi-directionality. In such instances, the algorithm swiftly identifies the nearest stop offering dual directions, optimizing the routing to prevent unintended detours and congestion. This strategic intervention ensures the seamless continuity of the rider's journey, circumventing potential disruptions and enhancing operational efficiency. The algorithm's capacity to anticipate and address these nuanced challenges underscores its efficacy in optimizing transit experiences and mitigating logistical complexities. Consequently, this algorithmic framework not only enhances rider satisfaction but also contributes to the sustainable management of public transit systems. Boarding at the ride-back start location, the rider embarks on a return journey to the initial destination, effectively concluding the simulated trip.

Statistics are systematically recorded both upon the initial release and the final disembarkation of the rider. Given the multidirectional nature of POIs, riders are equipped with binary indicators to denote departure or return to their home location. Furthermore, riders meticulously evaluate buses along the route, ensuring alignment with the intended direction. This strategic consideration prevents scenarios where riders board a bus close to downtown only to ride it out and then back, a behavior incongruent with human patterns. This comprehensive framework enhances the authenticity of the simulation, capturing the intricacies of rider decision-making and interactions within the urban transportation system.

The Point Of Interest (POI) agent encompasses fundamental parameters defining its role within the simulation. Its spatial coordinates, represented by x and y coordinates, establish its precise location on the Geographic Information System (GIS) map. Additionally, the POI agent is characterized by a route number, denoted as either route 40 or 17 and a binary indicator specifying its status as a starting point. The inclusion of the number of stops on the route and the capacity to discern its role as a starting point contribute to the comprehensive definition of POI parameters.

To accommodate the dynamic nature of bus routes on different weekdays, the POI agent incorporates a weekday parameter, ensuring accurate positioning within the temporal context. A binary value is employed to signify whether the POI is an ingress or egress point on the route. The directional attribute of the POI is a crucial aspect, considering

Algorithm 3 Determine Rider's Start Location for Return Journey

```
Retrieve a list of Points of Interest (POIs) for the return journey:
returnPOI = filter(main.pOIs17,
        e → e.direction == 2 or e.direction == −2 or e.direction == 0)
if rideBackStart.direction == −1 then
    Find the nearest POI along the return route:
    h = getNearestAgentByRoute(returnPOI)
    Original Return Start: + this.rideBackStart.stopNum
    Finding Nearest POI.......
    Best Return Start is Stop: + h.stopNum
    Update Rider's Start Location:
    rideBackStart = h
    Move Rider to the Updated Start Location:
    moveToInTime(this.rideBackStart, 0)
    Set Rider's Status:
    atStop = true
    isReturning = true
else if rideBackStart.direction == 1 then
    Find the nearest POI along the return route:
    h = getNearestAgentByRoute(returnPOI)
    Rider Name: " + this.RiderName
    Original Return Start: + this.rideBackStart.stopNum
    Finding Nearest POI.......
    Best Return Start for rider + this.RiderName + is Stop: + h.stopNum)
    Update Rider's Start Location:
    rideBackStart = h
    Move Rider to the Updated Start Location:
    moveToInTime(this.rideBackStart, 0)
    Set Rider's Status:
    atStop = true
    isReturning = true
else
    Output Rider Information:
    Rider Name: " + this.RiderName
    Original Return Not Changed: + this.rideBackStart.stopNum
    Set Rider's Status:
    atStop = true
    isReturning = true
end if
Set the ride-back destination to the initial start location:
rideBackDestination = start
Set the color of the rider's shape body to red:
shapeBody.setFillColor(red)
```

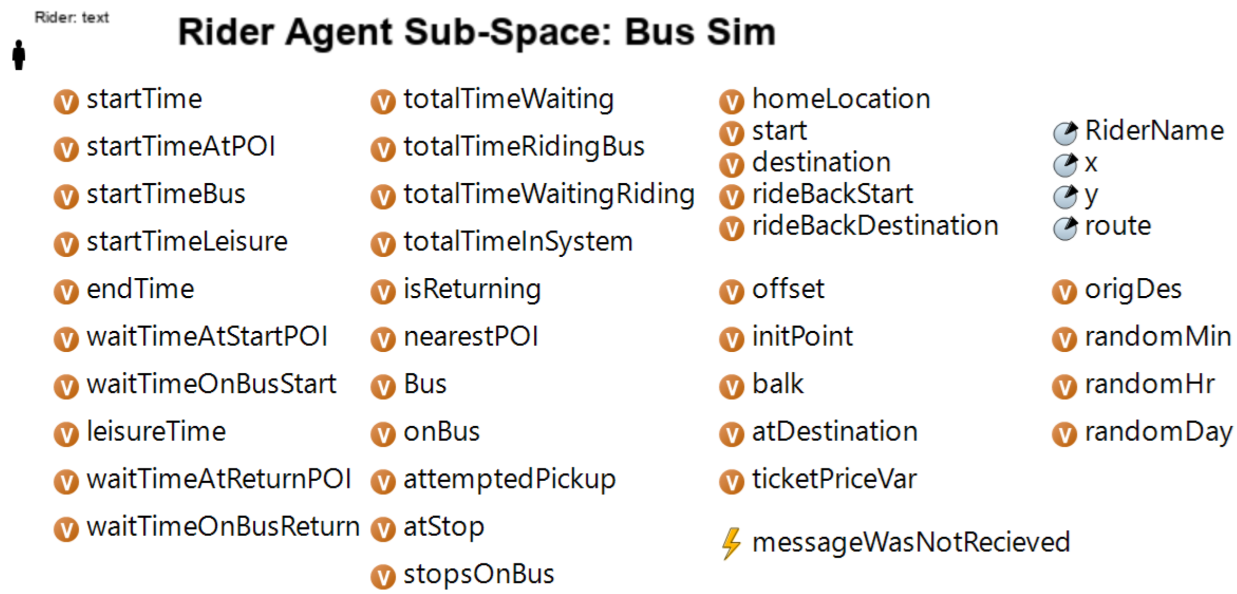

Figure 2.5: Rider Agent: Sub-Space (Bus Sim)

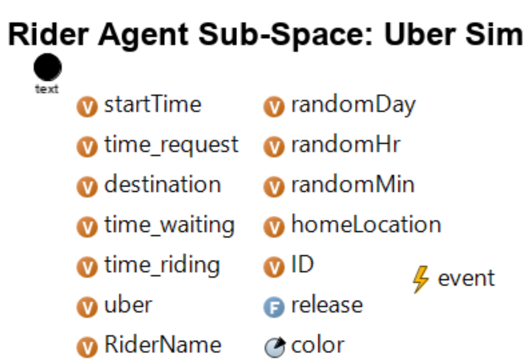

Figure 2.6: Rider Agent: Sub-Space (Uber Sim)

Table 2.5: Rider Variables

Variable	Type	Short Description
isReturning	Boolean	Shows if rider is on the way back or not.
rideTime	Double	Total time a rider spends on the bus.
onBus	Boolean	True if rider is on the bus, false otherwise.
Bus	Bus	Gives the bus the rider is on.
nearestPOI	POI	Gives the nearest POI to the rider agent.
attemptedPickup	Boolean	If the bus has been to that stop.
atStop	Boolean	True if the rider is at the stop, false otherwise.
stopsOnBus	Int	Total stops riders pass between their start and destination on the way out and back.
startTime	Double	Time buses start running, depends on the day.
waitTime	Double	Total time waiting for the bus for individual riders.
offset	Double	Value of (0.002) used to offset timing of riders from initialization to start moving.
initPoint	Point	The initial location riders will spawn at based on the tract data.
balk	Boolean	Initially false until rider balks then set to true.
atDestination	Boolean	Initially false but true when a rider gets to their respective destinations.
totalonBus	Int	Total riders riding on a bus.
homeLocation	Point	The location a rider starts at when the simulation is first initialized.
start	POI	This is the closest POI to the rider's home location, and therefore, this is the Stop the rider will start at.
destination	POI	This is the destination the rider is riding on the bus.
rideBackStart	POI	This is the starting location for riders after they have gotten off and are now waiting to return home.
rideBackDestination	POI	This is the final stop a rider will make. It will be the same as their original start.
origDes	POI	Gives original destination, which is randomly given.
ticketPriceVar	Double	Price of a ticket to ride one-way.

Table 2.6: Rider Parameters

Parameter	**Type**	**Short Description**
RiderName	Int	A unique index number given as a name to riders.
x	Double	X coordinate of rider's homeLocation.
y	Double	Y coordinate of rider's homeLocation.
route	Int	Value of which route to use.
ticketPrice	Int	Price of a ticket for a ride (1 USDA).

the presence of both bi-directional and unidirectional stops. This attribute dictates the subsequent movement of the bus after each stop, ensuring adherence to the prescribed route.

Critical for route navigation, the POI agent keeps track of the next stop and the next backstop, particularly in scenarios where the POI is bi-directional. This meticulous tracking is imperative for maintaining proper bus routing and adherence to the designated route path.

The final set of information encapsulated within the POI agent pertains to the number of people waiting at a given POI and a collection of these individuals. This streamlined approach facilitates the efficient boarding of individuals by bus, as it can readily identify and pick up those waiting at a specific POI. The collective attributes of the POI agent contribute to the overall realism and functionality of the simulation, aligning with the intricate dynamics of urban transportation systems.

Another agent is Tract information obtained from the US Census Bureau. In the context of the U.S. Census Bureau, "tract data" refers to demographic and socioeconomic information collected and organized at the level of census tracts. Census tracts are small, statistical subdivisions of counties or equivalent entities that are designed to be relatively homogeneous concerning population characteristics, economic status, and living conditions. Tract data includes various statistical measures and indicators related to the residents and households within these defined geographic areas.

Prominent demographic variables within tract data encompass key indicators reflecting the composition of populations within defined geographic areas. These variables typically include but are not limited to population size, age distribution, racial and ethnic demographics, educational attainment, and housing characteristics. Complementary to demographic aspects, socioeconomic indicators integral to tract data analysis comprise metrics such as median household income, poverty rates, employment status, and housing tenure, distinguishing between ownership and rental arrangements.

Within the scope of this simulation, specific data elements are utilized, serving as essential pointers for locating population information within highly specific tracts. These elements, including dex, statefp, countyfb, tractce, name, tractid, vintage, pop20, partial, and anylogic name, play a pivotal role as reference values facilitating precise identification of population characteristics. Certain elements, such as pop20, provide descriptive data,

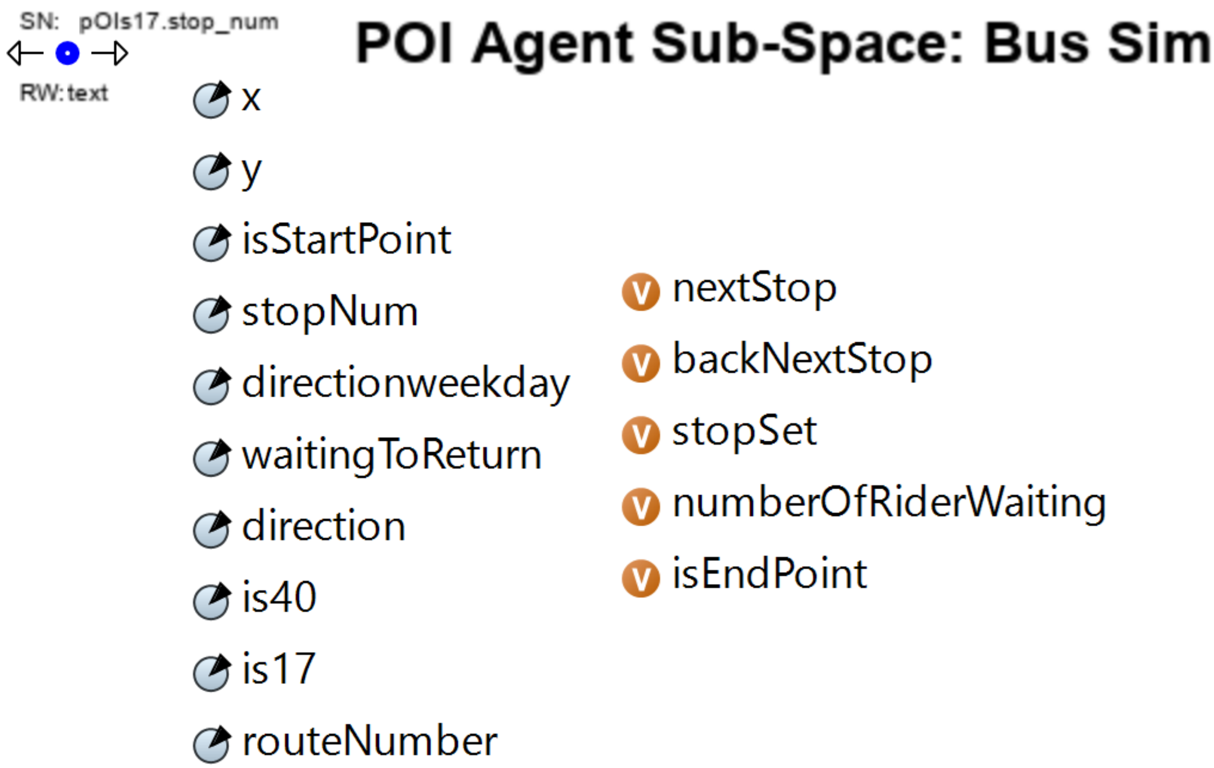

Figure 2.7: POI Agent: Sub-Space (Bus Sim)

Table 2.7: POI Parameters

Parameter	**Type**	**Short Description**
x	Int	The x coordinate for the stops (Longitude).
y	Int	The y coordinate for the stops (Latitude).
isStartPoint	Boolean	Sets the route sets so that not all routes are running at once.
stopNum	Int	Gives the POI's an Index to name them by.
directionweekday	Int	Gives the day as a value from 1 to 7.
waitingToReturn	Int	Gives the sum of riders waiting to return home at a stop.
direction	Int	Gives the direction the bus should be going. As it switches over the weekend.
is40	Boolean	Turns on or off bus route 40.
is17	Boolean	Turns on or off bus route 17.
routeNumber	Int	Gives the Route Name as its number.

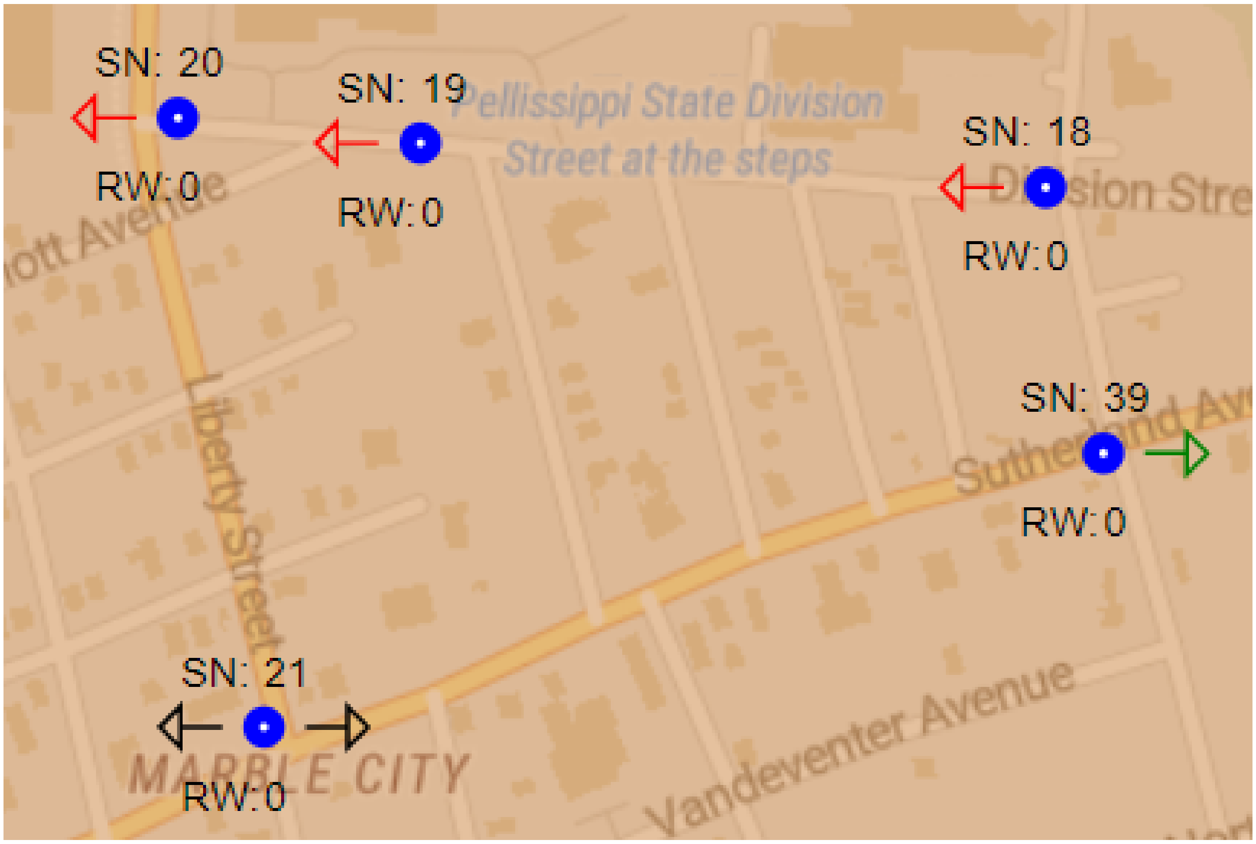

Figure 2.8: Muli-Directional Ability for POI

Table 2.8: POI Variables

Variable	Type	Short Description
nextStop	POI	Is the next stop the bus will be heading too.
backNextStop	POI	Is the Previous stop the bus was just at.
stopSet	Boolean	Sets the route sets so that not all routes are running at once.
numberOfRiderWaiting	Int	Sum of riders waiting at each stop.
isEndPoint	Boolean	Shows the bust at which point to return back down the route to the home base.

offering insights into the population size within a given tract, while others, like partial, delineate the proportion of individuals utilizing public transit services. Additionally, the dataset encompasses information on age, race, background, and economic status, providing a comprehensive understanding of the multifaceted demographic and socioeconomic landscape within these tracts. This nuanced dataset serves as a robust foundation for in-depth analyses and simulations, enabling a thorough exploration of urban dynamics and transit utilization patterns.

Tract data is valuable for understanding localized patterns and disparities within a region. Researchers, policymakers, and planners often utilize tract-level information to analyze trends, identify community needs, and make informed decisions related to resource allocation, urban planning, and social services.

This agent also encompasses all of the United States, and to download any information, one has to download a whole city, which a bus route does not always affect. So, within the simulation, there is a column that turns the tract visibility on and off, which is key to reducing clutter and runtime.

2.1.2 Interactions/Statecharts

The behavior of agents is established by their respective statecharts. In this context, a statechart refers to a procedural flow of operations that encompasses various states and transitions from one state to another. Each state defines the actions and behaviors of an agent at a specific point or within a particular circumstance. The states can be modified through transitions, allowing the agent to switch states based on various criteria. For example, a time limit for staying in a state or an object's arrival could trigger a transition to a different state.

The bus agent's statechart seen in 2.12 adheres to a typical public transit system flow. It initiates in a state that establishes its starting point, the depot. Once it is time for the bus's route to begin, it travels to the next Point of Interest (POI) on its designated route. Upon arrival at the POI, the bus reviews the collection of people on board and disembarks anyone whose destination POI matches the current stop. The state then changes according to a specified timing element, and the bus commences the process of picking up Person agents

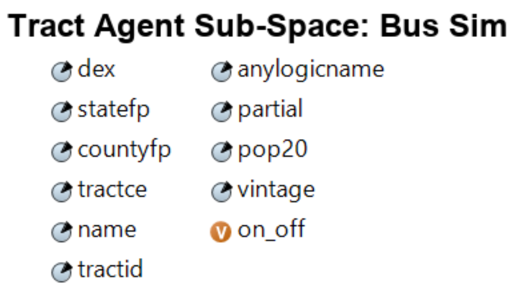

Figure 2.9: Tract Agent: Sub-Space (Bus and Uber Sim)

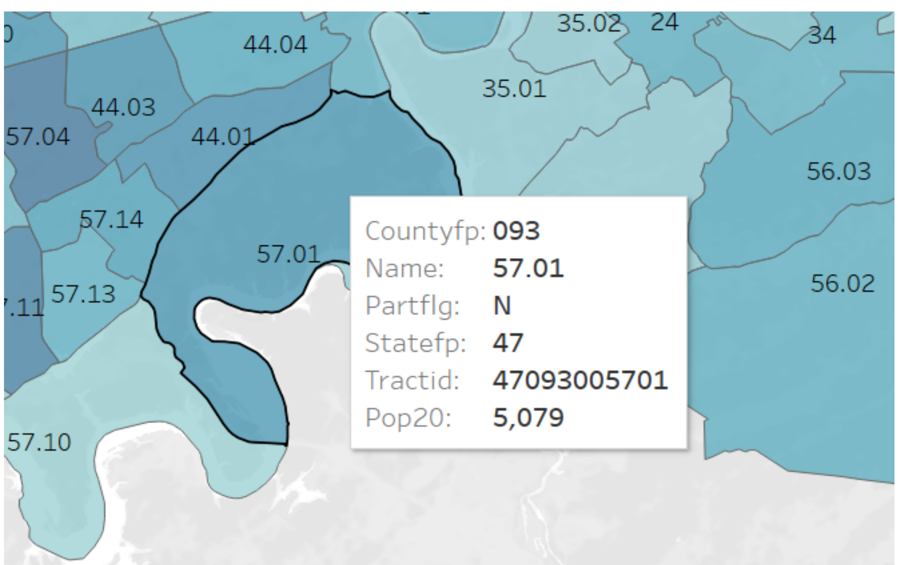

Figure 2.10: Visual of a Tract Located in Knoxville, TN

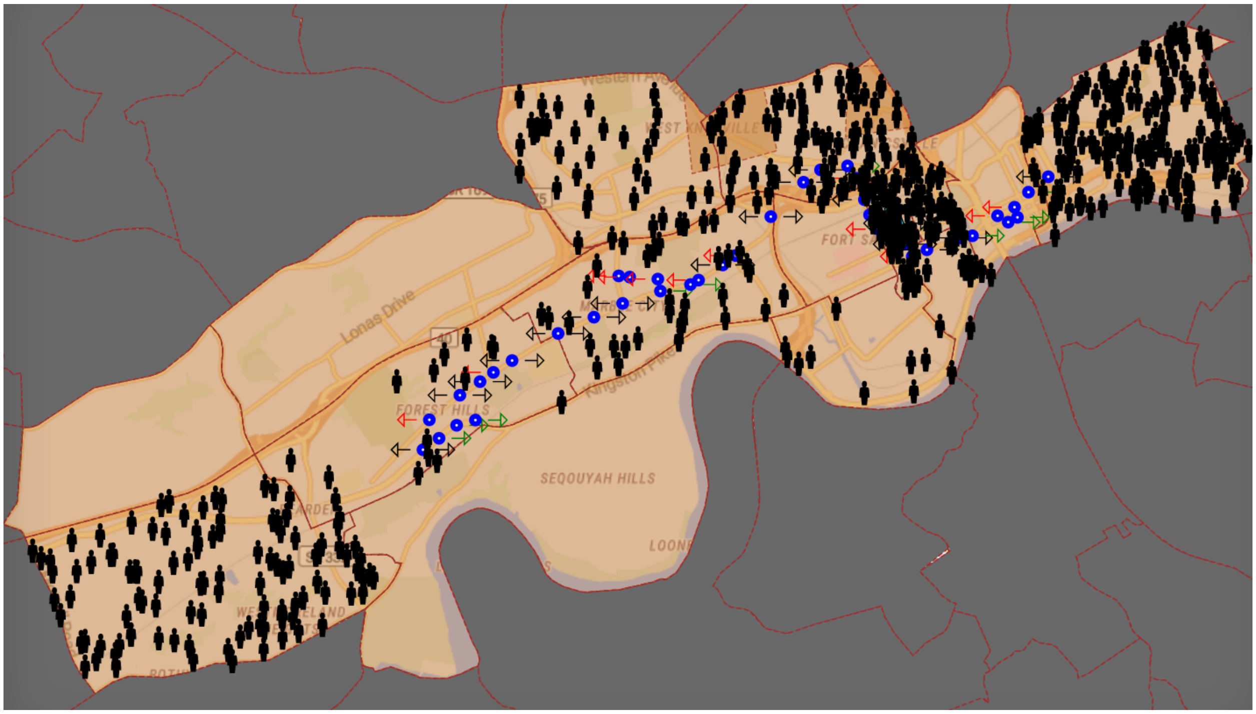

Figure 2.11: Visual of the agents populating their respective tracts.

Table 2.9: Tract Parameters

Parameter	**Type**	**Short Description**
dex	Int	An index to a region within the United States.
statefp	Int	An index to a state within a region within the United States.
countyfp	Int	An index to a county within a state in the United States.
tractce	Int	The population of the Tract.
name	Double	The truncated decimal naming convention by the US census.
tractid	Double	The entire numbered naming convention <dex><statefp><countryfp> of a tract.
vintage	Double	Old naming convention without decimal.
pop20	Int	population of the tract.
partial	String	Partial naming convention.
anylogicman	String	of tract given by Anylogic.

Table 2.10: Tract Variables

Variable	Type	Short Description
on_off	Boolean	A way to turn tracts on and off.

waiting at the current POI. Once the bus has loaded all the waiting people, it proceeds to the next POI in the sequence. This sequence repeats until the end of the working day, which is set at 1 am. The bus agent interacts with Person agents by functioning as their container as they travel from one location to another. Additionally, it interacts with POI agents as they serve as crucial stopping points for the bus. Overall, this process ensures that the bus agent's route remains efficient and serves as many people as possible.

The Rider Agent is configured for a fixed bus system, where it is created and initialized with necessary parameters at startup. The rider statechart is seen in figure 2.13. The agent moves to the designated start POI at a walking pace and waits at the bus stop. If the bus does not arrive before the balking transition occurs, the agent leaves the system, incrementing the balk counter. If the bus arrives on time, the agent boards the bus and rides to their intended destination. Upon exiting the bus, the agent updates their statistics to reflect their time spent in the bus system.

The time spent at the "Destination" is modeled using a triangular distribution with parameters (20, 120, 60), which appropriately represent rider behavior. Although a more precise distribution could be developed, the time spent at the destination is not critical for our analysis. After the delay, the agent returns to the stop they disembarked at and determines if the stop will take them closer to or further from their intended destination. The bus line operates as a linear route, not a circular one, stopping at all bi-directional stops but skipping those in the opposite direction. These skipped stops are serviced by another bus heading back or by the same bus on its return trip.

Once the rider identifies the optimal stop for their return journey, they move to that stop, change their color to red, and wait to be picked up by the bus. They then ride back to the original starting point. The starting stop can be either bi-directional or single-directional, so the rider must choose the nearest stop to their home that follows the bus's direction. If the start POI only sends riders away from downtown, it must be adjusted so riders choose the closest bi-directional stop to their original intended POI. Upon reaching their final stop, riders are released from the bus and subsequently deleted from the system to keep the model build and run times manageable.

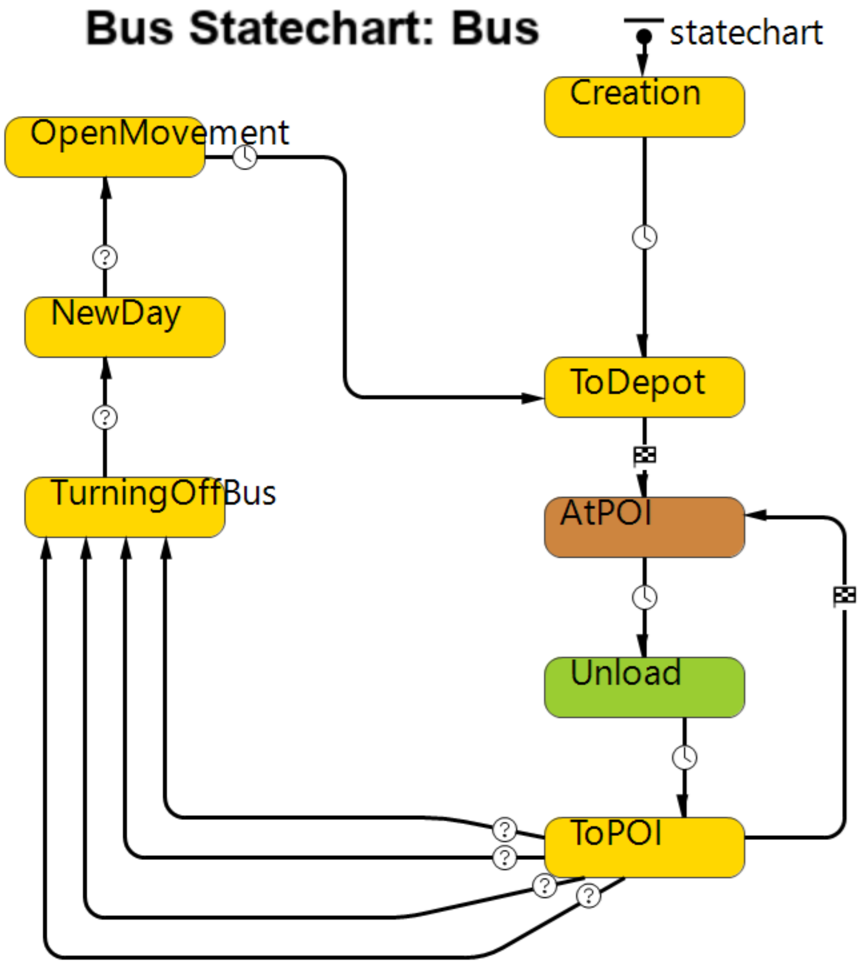

Figure 2.12: Statechart: Logic for bus to complete its route.

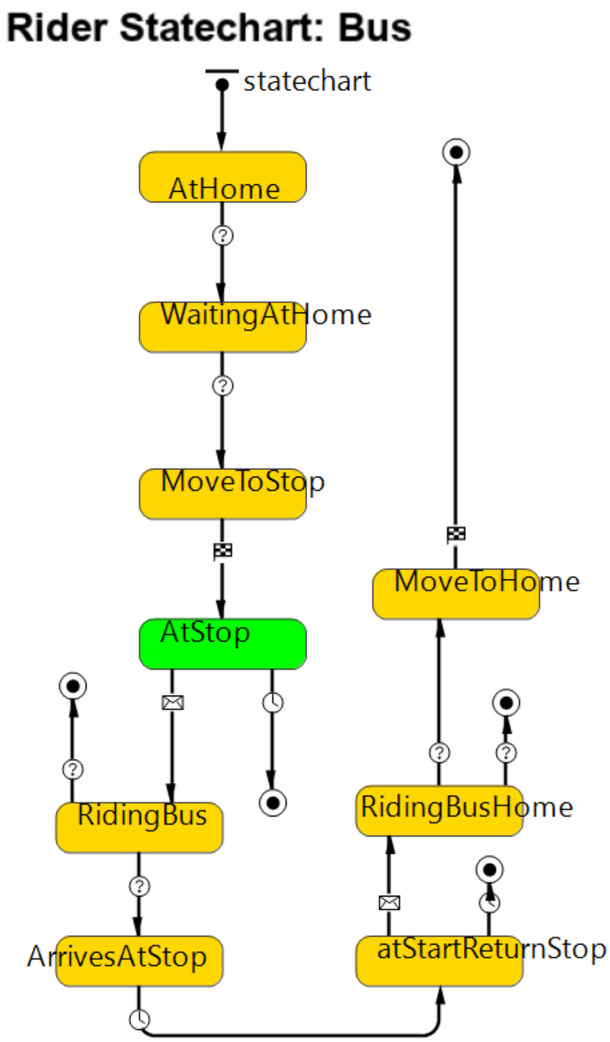

Figure 2.13: Statechart: Logic used to navigate the Bus route as a rider.

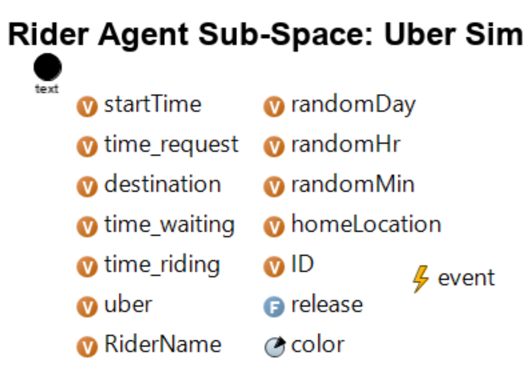

Figure 2.14: Statechart: Logic used to navigate the Uber System as a rider.

The POI agent is a location service, and thus, it does not contain a statechart. Its interactions with other agents are relatively straightforward. The Person agents walk to the POI and notify the POI once they arrive, prompting the POI to add them to its collection. The POI then interacts with the bus agent once it arrives at the POI's location. The bus goes through the collection of people at the POI, removes them from the collection, and adds them to the bus. This simple yet effective interaction between the POI, Person, and bus agents ensures efficient and seamless transportation.

2.2 Uber Simulation

The Uber simulation model contains many similar agents and behaviors to those present within the bus system. The differences are highlighted in the following sections.

2.2.1 Agents

Regarding the Uber system, the agents shared a multitude of characteristics with those in the bus simulation. However, there were slight differences that should be highlighted. The Uber itself solely had variables that pertained to its capacity, the number of riders, the collection of queued individuals, and the collection of people on the Uber. The collection of queued individuals held the list of people available for pick-up at any given time. The person agent remained the same, but instead of a start POI, it stayed in its spawned location. Furthermore, rather than a destination POI, it contained a destination hub. The hub agent shared similarities with the POI agent but contained less information and served only as an endpoint to the person's journey. The primary contrast between the hub and the POI was that the hub was a set location that wasn't along a predetermined route. A hub is described as a common place of interest (CPOI) that many people are likely to travel to, such as a mall, a nearby factory, a downtown city center, etc.

Below is algorithm 4, which is used to operate the Uber agent.

Algorithm 4 Uber Behavior

```
peopleInUber ← []
riders ← 0
while operating do
    if uber.queue.isEmpty() then
        wait()
    else
        for r in uber.queue do
            if uber.destination != null and uber.destination != r.destination then
                continue
            end if
            rider = uber.queue.pop(r)
            uber.destination ← rider.destination
            moveTo(rider)
            if rider.hasBalked then
                continue
            end if
            add rider to peopleInUber
            riders ← riders + 1
            if uber.queue is not empty and uber.sharedMode and uber.capacity > riders
            then
                continue
            else
                break
            end if
        end for
        moveTo(uber.destination)
        clear peopleInUber
        riders ← 0
    end if
end while
```

2.2.2 Interactions/Statecharts

The Uber agent's statechart seen in 2.15 flow begins with the Uber agent being idle, waiting for a Person agent to join its queue of individuals to pick up. Once a person is available for pick-up within the Uber's operating radius, it moves to collect them. At this stage, it either arrives in time to pick up the person or the person "balks" and declines the ride. If the person declines the ride, the Uber agent starts the process anew. Conversely, if the person agrees to the ride, the Uber agent evaluates if there are other eligible individuals within its operating radius who are heading to the same hub, assuming it is a shared Uber. If there are, they are subsequently picked up. This process continues until either the Uber agent has reached its capacity or there are no more individuals that meet the criteria for pick-up. The FIFO (First-In-First-Out) Uber agent, however, skips this stage.

From there, the Uber agent takes the person or people to the designated hub and drops them off. The Uber agent then re-evaluates whether there are any additional eligible individuals for it to pick up. If there are, the cycle restarts; if not, the Uber agent simply becomes idle in its current location. This process enables the Uber agent to continually serve the community and transport individuals efficiently to their intended destinations.

For dial-a-ride system users, the person seen in figure 2.16 is created, and necessary parameters are defined at startup. The agent then requests a ride and awaits assignment to an Uber. If the Uber does not arrive before the balking time threshold is reached, the person will leave the system while incrementing the balk counter. However, if the Uber arrives before the threshold, the person boards the Uber and rides until they are dropped off at their desired POI. Following this, the person exits the Uber, updates their statistics to accurately reflect their time within the KAT system, and is removed from the simulation. These state charts ensure that the Person Agent operates smoothly and efficiently within the KAT system, enabling seamless transportation for fixed routes and dial-a-ride users alike.

2.3 Combined Simulation

The combined bus and Uber simulation represents a sophisticated integration of two previously distinct models. To achieve this, the existing bus simulation framework was

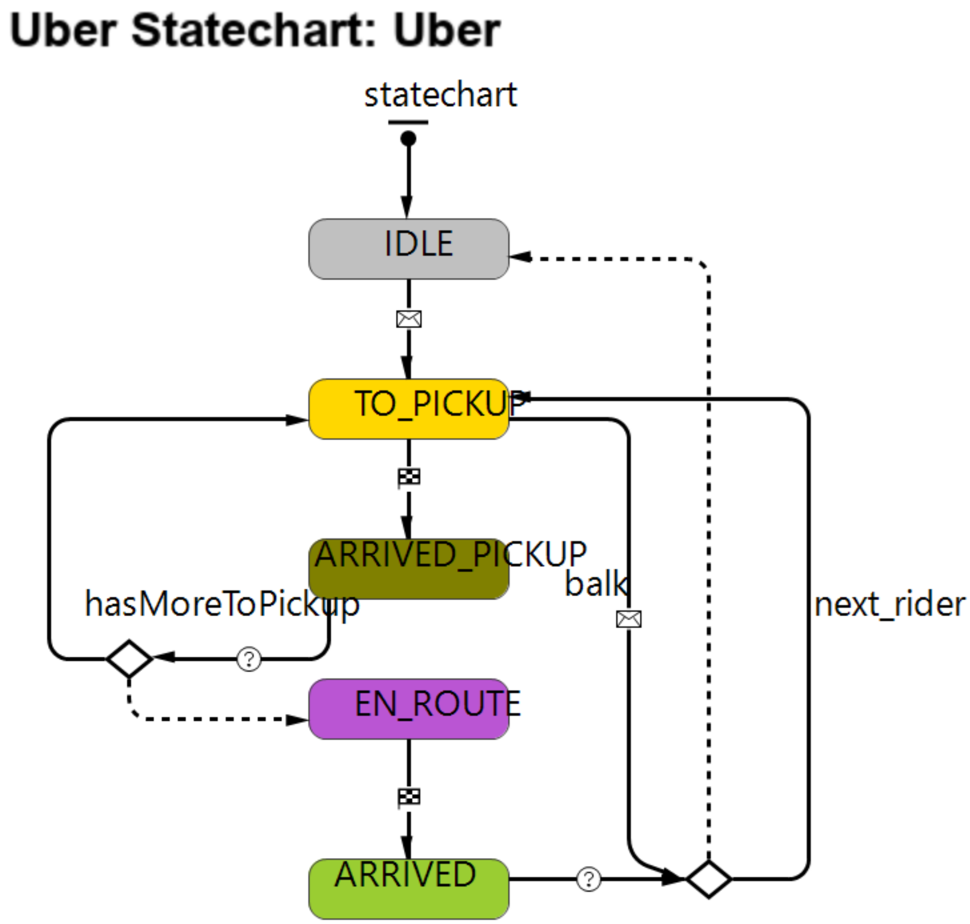

Figure 2.15: Statechart: Logic used to navigate the Ubers to riders.

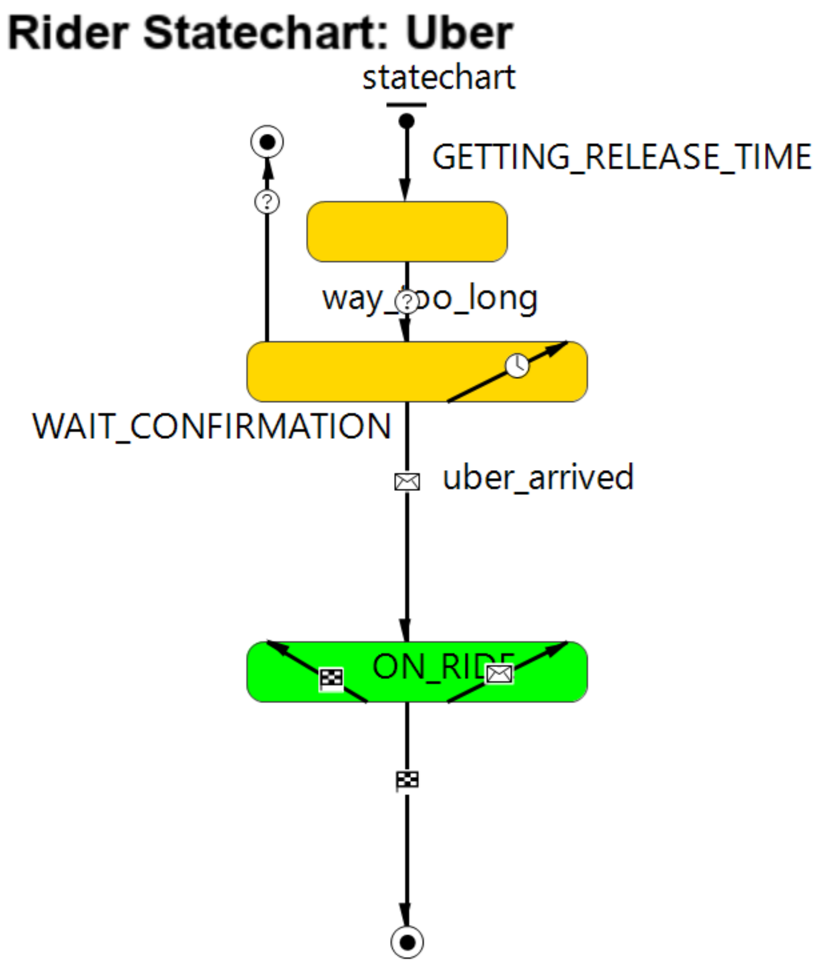

Figure 2.16: Statechart: How the user of the Dial-a-Ride operates.

expanded to incorporate the Uber simulation. This integration presented numerous challenges, notably the errors generated by AnyLogic due to the disparate Java containers housing the original projects.

A notable feature distinguishing the combined model from the individual simulations is the introduction of dynamic demand. This adjustment is managed through a function called *adjustRateRequestPerHour*. This function modulates the rate at which riders are introduced into the system based on their wait times. Specifically, if the average wait time increases by 2 minutes, the request rate decreases accordingly. This adjusted request rate then determines the scheduling of events that generate new agents, using the formula exponential(RATE_REQUEST_PER_HOUR/60).

In this model, an increase in wait times leads to a decrease in rider arrival rates and vice versa, effectively illustrating the impact of fluctuating demand on the system. This dynamic demand mechanism influences both the bus and Uber systems. For example, if an Uber rider experiences excessive wait times and decides to balk, they are redirected to the bus queue in an attempt to complete their journey. Conversely, if a bus rider balks, they are transferred to the Uber queue, where they either wait for a ride or, if wait times remain excessive, exit the system entirely.

All agents within the simulation retain their original characteristics, with the exception of the newly introduced demand variability. This variability is critical for capturing the interdependent nature of rider behavior and system performance. As illustrated in figure 2.17, the interactions between agents in the combined model create a comprehensive representation of the transportation system, highlighting the intricate dynamics and dependencies inherent in real-world scenarios.

This combined simulation not only enhances the understanding of individual system behaviors but also provides a robust platform for analyzing the effects of dynamic demand on transit operations. By integrating the bus and Uber models into a single cohesive framework, the simulation now offers a comprehensive view of the entire transportation system. This holistic approach allows for a more accurate representation of real-world scenarios where different modes of transportation interact and influence one another.

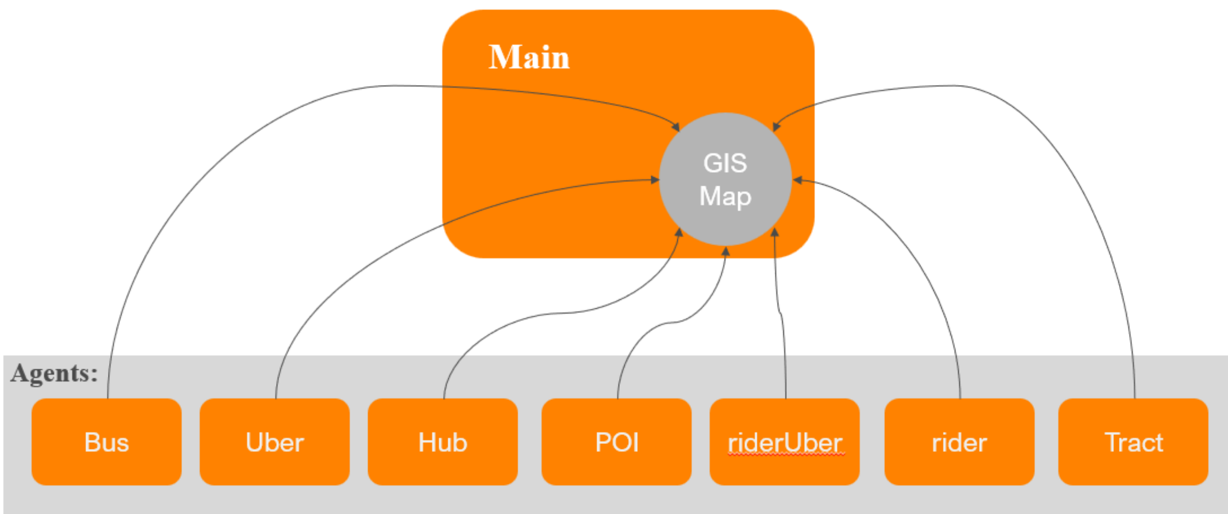

Figure 2.17: Shows agent connections within the simulation.

The introduction of dynamic demand within the simulation is particularly significant. As wait times for one mode of transportation increase, the rider arrival rate adjusts accordingly, reflecting the natural ebb and flow of passenger preferences and behaviors. This dynamic interplay between supply and demand can now be observed and analyzed in detail, providing deeper insights into how fluctuations in demand impact overall system performance.

Moreover, the combined simulation can effectively model the behavior of riders who switch between bus and Uber services based on wait times and availability. This aspect is crucial for understanding the flexibility and adaptability of the transit system in meeting the needs of passengers. For example, when Uber riders experience long wait times and decide to switch to the bus service, or vice versa, the simulation captures these transitions and their effects on both systems.

The ability to simulate such interactions and dependencies between different transportation modes represents a significant advancement in transportation modeling. It enables researchers and planners to explore various scenarios, assess the impact of different variables, and develop strategies to optimize the performance and efficiency of public transit systems. By providing a more nuanced and integrated view of the transportation network, this combined simulation serves as a powerful tool for enhancing the planning, management, and operation of urban transit systems, ultimately contributing to the development of more resilient and responsive transportation infrastructures.

Chapter 3

Experiments

3.1 Case Study

KAT is the public transportation system in Knoxville, Tennessee, and it serves a population of around 186,000 people in the city and surrounding areas. The bus system consists of over 20 fixed routes and paratransit services for disabled individuals.

One of the challenges faced by KAT is low ridership, with only around 2 percent of the population using the bus system on a daily basis. In an effort to increase ridership, KAT has implemented several initiatives, such as expanding service hours, introducing new technologies like real-time bus tracking and mobile ticketing, and increasing the frequency of buses on popular routes.

Another challenge for KAT is funding. Like many public transit systems, KAT relies on a combination of federal, state, and local funding to operate. However, these sources of funding can be unpredictable and insufficient, leading to difficulties in maintaining and improving the bus system.

This study analyzed the performance of the Knoxville Area Transit (KAT) system, specifically the static bus route, and evaluated its efficiency and effectiveness. The results showed that the demand response, which is the total number of passengers, fluctuated between different months and years. For example, in October of 2022, the demand response was 6,387, which is 2 percent lower compared to October of 2021 (6,502). However, in September of 2022, the demand response was 6,505, which is 2 percent higher compared to

September of 2021 (6,380). In August of 2022, the demand response was 7,055, which is 11 percent higher compared to August of 2021 (6,357).

Revenue vehicle miles, which is the distance traveled by vehicles while generating revenue, generally increased. In September of 2022, the revenue vehicle miles were 43,603, which is 4 percent higher compared to September of 2021 (42,015). In August of 2022, the revenue vehicle miles were 46,897, which is 8 percent higher compared to August of 2021 (43,588). System-generated revenue, however, showed fluctuations between different months and years. For example, in October of 2022, the system-generated revenue was 70,839, which is 70 percent higher compared to October of 2021 (41,707). In August of 2022, the system-generated revenue was 19,652, which is 5 percent lower compared to August of 2021 (20,701).

The number of passengers per mile, which is a measure of passenger density, generally decreased. For example, in October of 2022, the number of passengers per mile was 0.15, which is 5 percent lower compared to October of 2021 (0.16). In August of 2022, the number of passengers per mile was 0.15, which is 3 percent lower compared to August of 2021 (0.153). Moreover, the number of preventable accidents, which are accidents that could have been avoided, generally increased between different months and years. For example, in October of 2022, the number of preventable accidents was 2, which is 200 percent higher compared to October of 2021 (0).

The Knoxville Area Transit (KAT) system, based in Knoxville, Tennessee, has the potential to improve its efficiency and effectiveness. An analysis of the system found that the fluctuation in demand response and revenue generated suggests a need for better scheduling and route optimization. Additionally, the decreasing number of passengers per mile and the increasing number of preventable accidents highlight a need for better safety measures and increased passenger density.

To address these challenges, the study recommends that KAT consider implementing new technology, such as demand-responsive transit, to improve efficiency and safety. KAT has also sought out partnerships and sponsorships with local businesses and organizations, such as the University of Tennessee, to provide discounted fares for students and employees. The bus system has also received grants from the Tennessee Department of Transportation and the Federal Transit Administration to fund specific projects and improvements.

Despite these initiatives, KAT is still facing challenges in increasing ridership and securing stable funding. However, the study provides valuable insights into the KAT system and suggests areas for improvement that can benefit both the system and the community. Overall, KAT is working to address these issues through a variety of approaches and partnerships.

3.1.1 Case Study: Variations and Examples

As Knoxville continues its efforts to improve its transit system, other cities have already taken the lead in implementing innovative solutions. Atlanta, GA, for instance, has established a dial-a-ride system called MARTA Reach, which has been met with overwhelmingly positive reviews. This dynamic system, however, only delivers within a specific zone, limiting its range. To address this constraint, the static routes to all parts of the city remain operational, ensuring that no customers are stranded within their respective zones [52].

On the other hand, Charleston, SC's transit authority, CARTA, has adopted a different approach by introducing OnDemand, a partnership with Uber. In this system, customers can use Uber services at a reduced rate subsidized by CARTA. This innovative solution has resulted in increased revenue for the city and required virtually no new infrastructure, as the existing Uber system can handle the demand [20].

Similarly, the city of Denton, TX, plans to implement a dial-a-ride system to completely replace its fixed-route service, bringing it closer to our proposed plan of a shared uber-like system to supplement rides. By examining these alternative transit models, our research aims to inform the development of a more efficient and effective public transportation system for Knoxville and similar medium-sized cities [27].

Given that many municipalities across the USA are looking for more viable forms of public transit to effectively serve their populations, a simulation tool like the one developed in this study can have enormous impacts in assessing the potential benefits of dial-a-ride systems. The simulation's adaptability to different cities is enhanced by Anylogic's GIS map system, which allows users to add shape files and integrate data from the US Census Bureau. Users can implement the simulation for any city and run analyses based on population statistics available from [18]. This tool can be used to determine whether small, medium, or large cities would benefit from incorporating a dial-a-ride system into their current transit infrastructure.

Later in this paper, we will discuss how such a system could greatly benefit a medium-sized city with low demand, such as Knoxville, TN. Conversely, for cities like New York City, which have extremely high demand and limited road access, a dial-a-ride system might negatively impact the overall transit system. However, it could still be beneficial for specific use cases, such as providing transportation for individuals with disabilities to help them reach their desired locations.

3.2 Simulation Settings

3.2.1 Base Model

The base model was originally evaluated through two scenarios: a single route and a combination of two routes. We must first discuss the combination of routes scenario. This gave insight into how the system operated in a more real-life scenario. However, the insight was extremely minimal, and often times, the simulation could not run, as it had too many agents to keep up with. A problem that expedited this was the way in which the riders found their nearest agent when trying to optimize their routes. Anylogic uses an API to find the routing for its agents, but this call is limited to 20 routes returned a second. The API calls for every possible route a specific agent can follow to its destination. This means every agent must check over 150 different routes for each movement to the nearest agent. This starts to add up very quickly until the model takes weeks to run. After calculating the time to complete a single run, it would take almost two weeks. This is the reason that the base model will not contain multiple routes. The value added was also minimal, as keeping it in the system would not give any more insight than just one route. So because of this, it was left out of further analysis. By doing this, we allowed for the confirmation of real-life trends and a more accurate portrayal of the KAT system's relationship with its customers. By establishing an accurate model, the simulation could then be used to generate new ideas and potential solutions that could outperform the current KAT system.

For accurate results to come from the base model, it must be configured in accordance with the real data given by KAT. The first scenario we looked to simulate was the standard bus route 17 in Knoxville. This route follows Sutherland Avenue, a relatively busy side street that is located just outside of downtown Knoxville. This route was chosen based on its usage and location. It is one of the busiest bus lines in Knoxville with around 10 riders per hour [52]. Its location is also important as it is just outside downtown and portrays the widespread nature of Knoxville. To find the simulation settings that most accurately portrayed the results of the real-time route, many iterations were run with different initial parameters. The parameters that were decided are shown in table 3.1.

To accurately portray the KAT system for route 17, it was determined that 2 buses must be running at a time like the actual system. This was based on information found about the route from KAT resources [52]. According to the KAT schedule, these buses needed to be 30 minutes apart from each other, as that is how it is scheduled. The overall time of the route was a one-hour round trip. Some tuning of the time at each stop was done to create an accurate duration of the bus trip. The person arrival rate was determined using the US census location tracts. A tract is an area on a map that the US census tracks and keeps records of. The tract gives Population and Population Usage. Using these, we can determine an arrival rate for rider agents.

3.2.2 FIFO & Shared Uber

The simulations for both the FIFO and Shared Uber models shared the same simulation parameters and settings as seen in 3.2. The key difference between the two models was that the Shared Uber model took into account the capacity of the vehicles, while the FIFO model treated each rider as a separate service.

The base model was established using historical data from KAT, but since there was no historical data available for Uber systems, a baseline set of parameters was defined and adjusted based on the impact of each parameter on the simulation. The Uber systems had several parameters that were used to configure the simulation, including capacity, mode, speed, distance delta, number of Ubers, and waiting threshold. Like the base model, these models also create riders based on the tract data. This was shown to be a helpful thing as it more closely relates to the two different models.

Table 3.1: Simulation Settings for the base model.

	num_routes	num_buses	bus_arrival	person_arrival
Route 17	1	2	30 minutes	0.03225806

Capacity refers to the number of ride requests that can be serviced by a single Uber. Mode specifies whether the simulation is running a Shared or FIFO Uber. Rate request per hour determines the number of ride requests that enter the system each hour, and a distribution from the US census is used to simulate more realistic request patterns. Speed refers to the average speed of the Uber vehicles. Distance delta defines the radius around each Uber within which it will accept ride requests. Number of Ubers refers to the total number of vehicles within the system. Finally, the waiting threshold specifies the maximum amount of time a ride request will wait before it is cancelled.

Overall, the parameters were carefully chosen to accurately simulate the behavior of the Uber system and to explore how different settings can impact its efficiency and effectiveness. The baseline parameters for the Shared and FIFO Uber system are shown in table 3.2.

3.2.3 Combined

This simulation integrates the shared Uber service with a bus line, using the same baseline parameters as the individual bus and shared Uber models. The bus baseline parameters are detailed in Table 3.1, and the shared Uber baseline parameters are listed in the shared row of Table 3.2. The primary distinction of this combined simulation is the ability to observe the impact of Uber services on an already established bus route, providing valuable insights into the overall effectiveness of the integrated transit system.

A significant enhancement in this simulation is the introduction of dynamic demand. The demand model continues to follow the tract data for riders along the bus route to maintain realistic system behavior. Additionally, variability in demand is introduced by adjusting the injection rate of agents based on wait times. Specifically, when wait times are high, the rate of agent injection slows down, and conversely, when wait times are low, the rate speeds up. This approach ensures that the simulation accurately reflects the dynamic nature of rider behavior.

Wait time has been identified as a critical factor influencing rider decisions. Lower wait times attract more riders to the system, simulating an increase in user adoption as the system improves in efficiency. Conversely, higher wait times discourage ridership, reflecting a natural decline in usage due to system overcrowding. This demand variability is crucial

Table 3.2: Simulation Settings for FIFO and Shared Uber Simulations

Mode	Capacity	Rate Request per Hour	Speed	Distance Delta	Number of Ubers	Waiting Threshold
FIFO	1	20	45 mph	0.04 GIS	4	30 min
Shared	4	20	45 mph	0.04 GIS	4	30 min

for simulating real-world scenarios where public transit usage fluctuates based on service quality.

By incorporating these elements, the combined simulation offers a comprehensive view of how Uber services can complement traditional bus routes, enhancing our understanding of integrated transportation systems. This approach not only provides theoretical insights but also practical implications for optimizing urban transit networks to better meet the needs of the population.

3.2.4 Optimization

The use of AnyLogic and AnyLogic Cloud provided a range of powerful simulation tools and features that were critical to optimizing the Shared and FIFO Uber simulations. By leveraging the power of the cloud, the simulations could be quickly deployed and run online with minimal hardware constraints, which allowed for a more rapid and efficient optimization process.

One of the key benefits of using the AnyLogic Cloud for optimization was its ability to provide powerful tools for comparing the results of different simulation runs. Since the simulations involved the manipulation of multiple parameters, the ability to compare and contrast the results of different runs was essential for identifying the optimal models. With the AnyLogic Cloud, the results of each simulation could be easily visualized and overlaid on graphs, which allowed for inferences to be drawn and for trends to be identified.

Furthermore, the AnyLogic Cloud allowed for the simulations to be run at scale, which was critical to ensuring that the models were accurate and robust. By running the simulations on a larger scale, it was possible to identify patterns and trends that would not have been apparent in smaller-scale simulations. This allowed for the optimization process to be more comprehensive, resulting in a more accurate and effective model.

In addition, the AnyLogic Cloud also provided a range of powerful tools for configuring and adjusting the simulation models. These tools made it easy to adjust various parameters and settings, which allowed for a more flexible and adaptable optimization process. This was particularly important for the Shared and FIFO Uber simulations, which involved complex algorithms and models that required frequent adjustments and modifications.

3.3 Results

The results for the different systems were gathered using the Anylogic model that was developed for the case study of Knoxville. The metrics used to evaluate the different systems were the wait time, ride time, balking rate, and in the bus case, the utilization of the system. The wait time is an important metric as it measures the amount of time the person spends in their wait for service. Shorter wait times and ride times equate to better customer satisfaction and more confidence in the system overall. The balking rate is also important to analyze as it shows the percentage of people who wait too long. Having a high balking rate shows a system is under-serving its users and will deter people from using the system in the future. Based on these metrics, a conclusion of the best system for this type of city can be made.

3.3.1 Bus Model Results

The results of the two base scenarios are presented in this section. These results were gathered based on runs of the formulated simulation. For each scenario, the simulation was run for a one-month-long period to find the most accurate daily results. These results were first confirmed with the real data that was available through KAT and the US Census Bureau before collecting the rest of the results of the simulation. Consequently, our simulation falls into the category of a soft digital twin, as it is not linked to a live data feed. If the simulation were controlled by live data, it would qualify as a true digital twin. We opted for this approach to ensure that the simulation remains broad and adaptable, allowing it to be easily applied to the simulation of other bus lines. This broader perspective facilitates a more comprehensive optimization strategy, enhancing the overall utility of the simulation.

Baseline

The simulated run determined an average of 1.32 riders per hour per bus. This simulation yielded several descriptive statistics, which are detailed below.

The number of riders that can be found on the bus at any given time is shown in Figure 3.1. The figure illustrates that the most likely number of people on the buses at any given time is around 2. The histogram bins indicate that approximately 30 percent of the time,

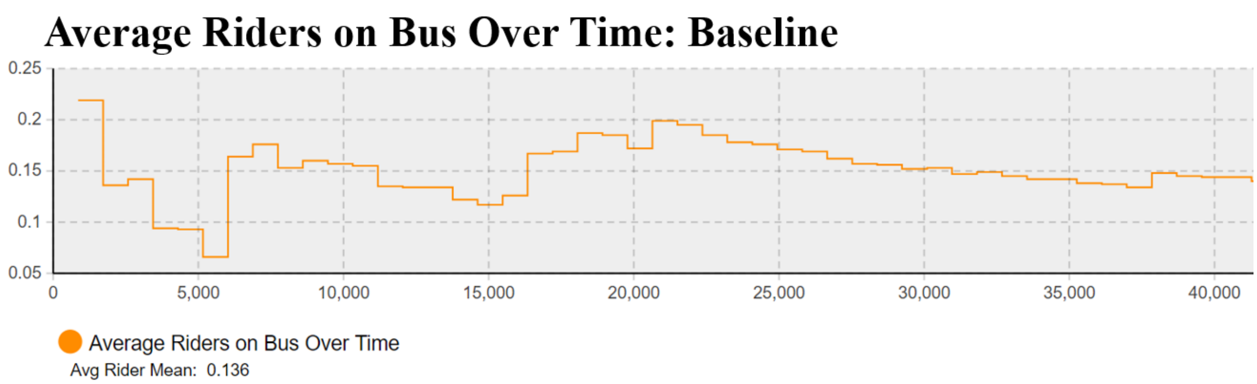

Figure 3.1: Average Riders on Bus at Time

there are between 2 and 3 people on the buses. With the majority of the time having fewer than 6 people in total riding the buses, it can be inferred that the KAT system does not adequately serve its constituents in this area. The ridership falls short of expectations for a system well-funded through the government.

Figure 3.2 presents the average utilization of buses. The results indicate that the buses are operating at around 1.36 percent for any individual bus on average. This low utilization further supports the observation that while the system services the customers who use it efficiently, it fails to attract a larger user base. The urban sprawl of the city contributes to this issue, as the system itself is not inherently inefficient but rather suffers from a lack of patronage.

As shown in Figure 3.3, the average bus utilization fluctuates but generally remains below optimal levels. This figure indicates that, over time, the buses maintain an average utilization below the desired threshold, reinforcing the need for strategies to increase ridership.

In reference, Figure 3.4 displays the average riding times for different segments of a rider's journey. The average riding time is 40.95 minutes, with the average time from the start to the destination stop being 25.87 minutes and from the destination to the home stop being 60.06 minutes. One reason for the observed variance in these numbers is that riders heading home must decide whether to get off at their original start stop or a different stop if the bus route is moving away from their desired destination leading to an increased ride time. This data suggests that while the system is effective in transporting riders, the total time spent on the bus can be substantial, potentially impacting rider satisfaction and the perceived efficiency of the system.

Figure 3.5 displays the average wait times for riders. The average wait time is 35.55 minutes, which is relatively short for public transport. Despite the buses being 30 minutes apart, the system manages to maintain an acceptable wait time for its users. This data suggests that the system is efficient in servicing the users it has but needs improvements in attracting more riders.

Figure 3.6 illustrates the percentage of riders served versus those who balked. The chart shows that 59 percent of potential bus riders utilize the bus service, while 41 percent do not. This indicates that while the system is effective for a majority of users, there is still a

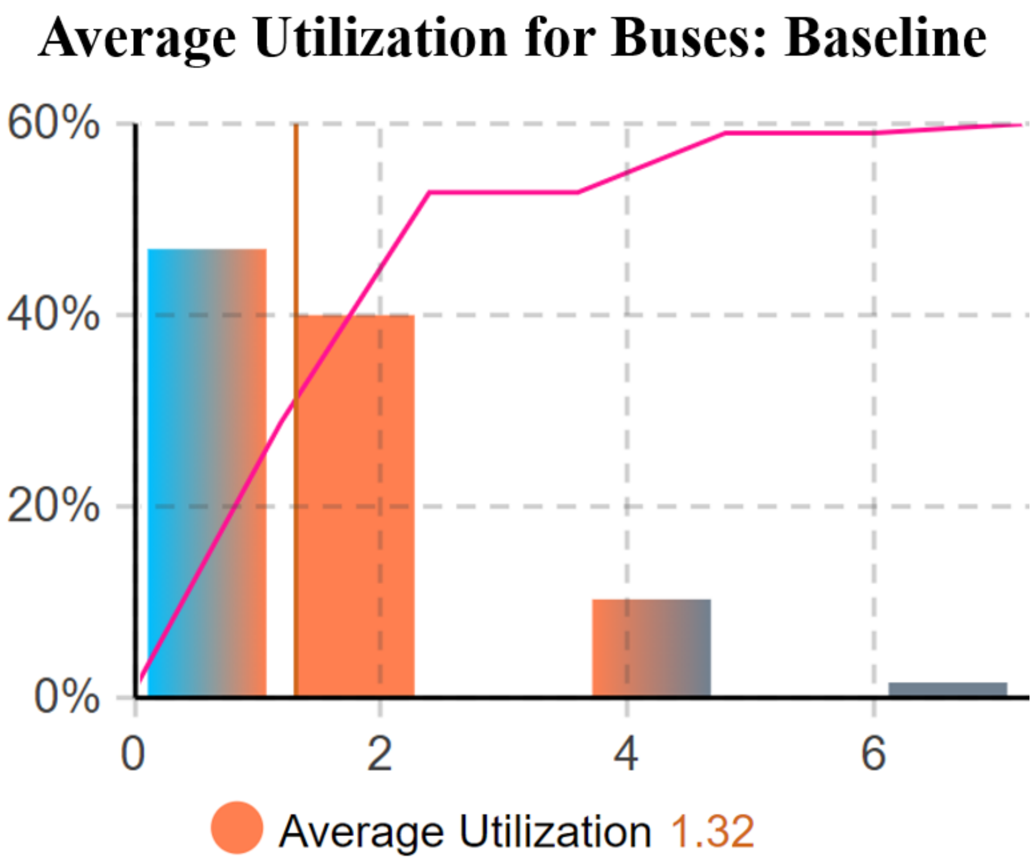

Figure 3.2: Utilization of Route 17

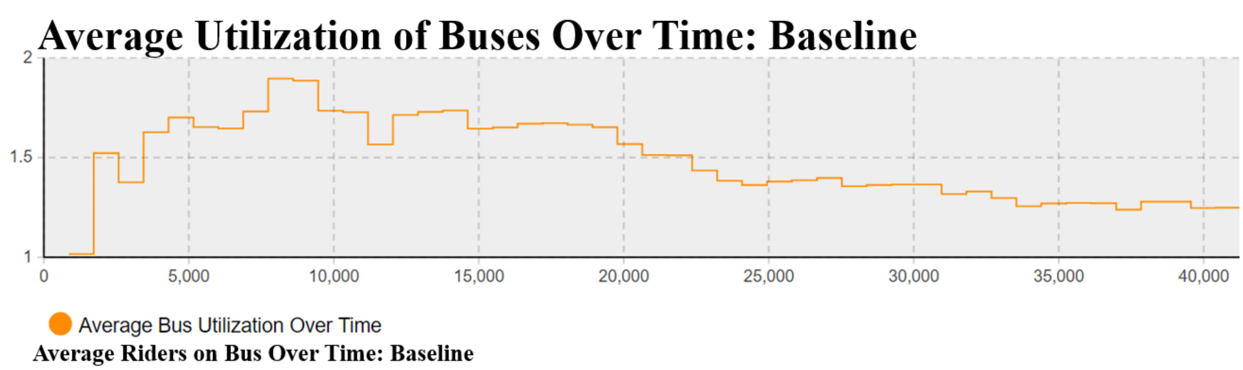

Figure 3.3: Average Bus Utilization Over Time

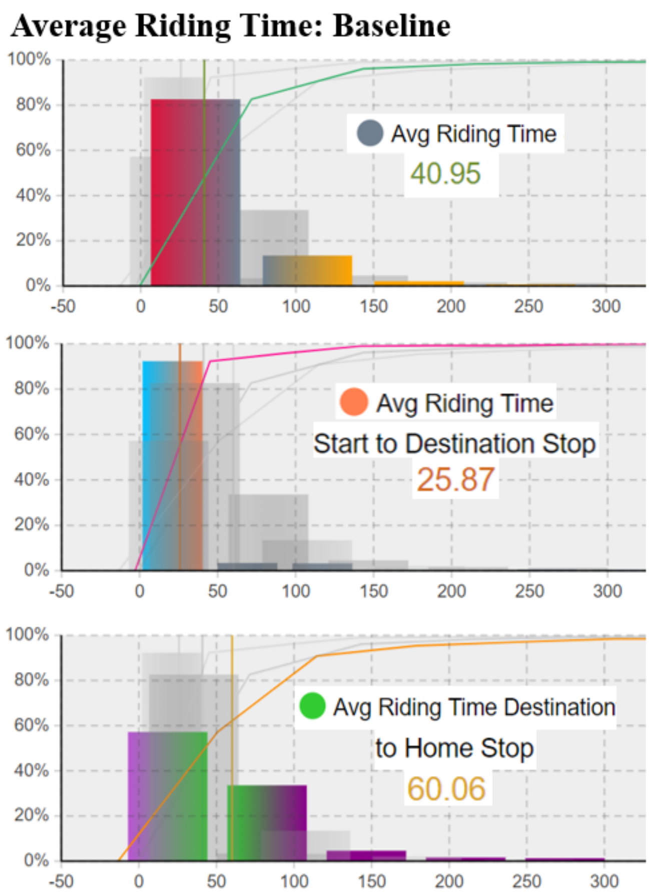

Figure 3.4: Average time rider spends on a bus.

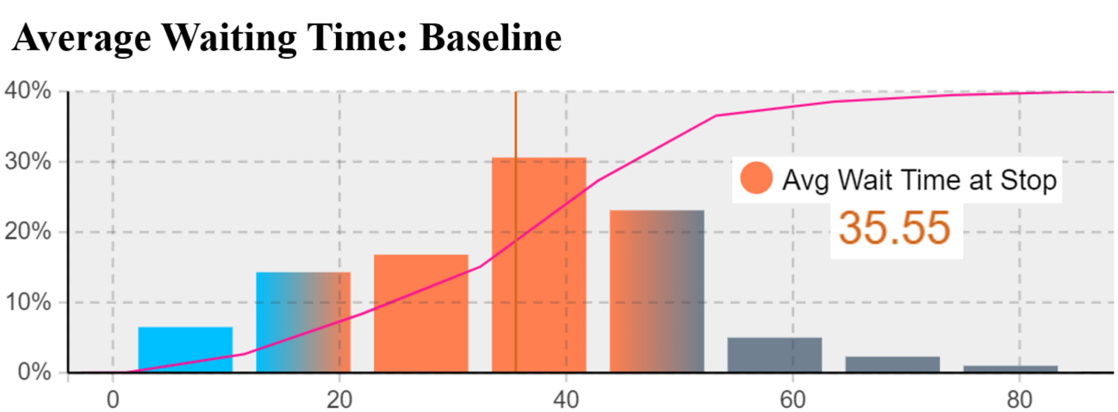

Figure 3.5: Average time a rider waits at the stop before being picked up by a bus.

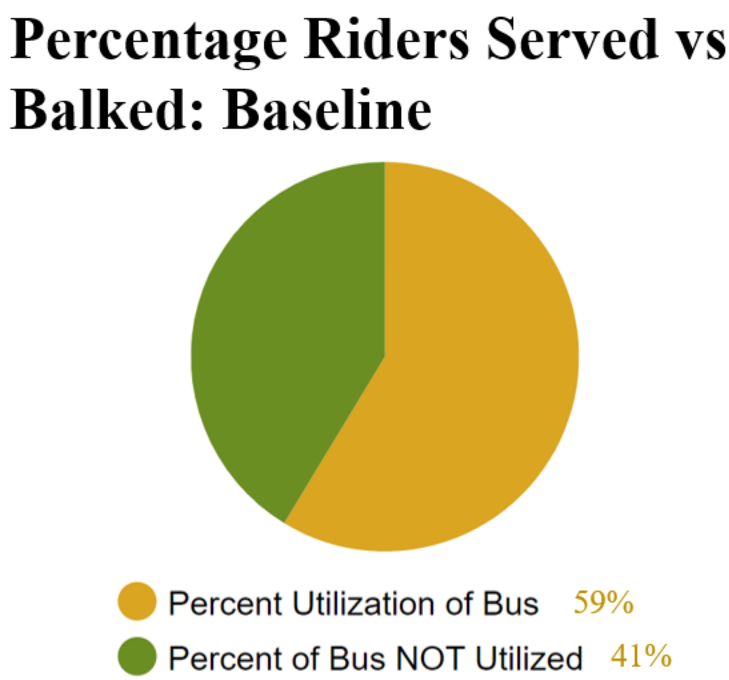

Figure 3.6: Percentage of riders balking from system or served

significant portion of potential riders who choose not to use the service due to factors such as wait times, bus stop locations, and route efficiency.

Overall, the KAT system appears to perform well in servicing the current users but struggles with low ridership numbers. This is likely due to urban sprawl and not the system's inefficiency. Improving the system's appeal and accessibility could potentially increase utilization and provide better service to a larger portion of the city's population.

These figures provide a visual representation of the described statistics, reinforcing the conclusion that while the system is efficient for current users, it requires enhancements to attract more riders and serve a larger portion of the population effectively.

Sensitivity Analysis

The simulated runs provided insightful data on the utilization of the KAT system, offering a comprehensive look at its performance. Previously, we focused on the baseline model with 2 buses. However, the sensitivity analysis section allows us to compare different scenarios by varying the number of buses from 1 to 6, as this was truly the only controllable variable that had significance to the system. The following sections present and analyze the key statistics derived from these simulations, highlighting areas for potential improvement.

The average percent utilization of buses over time indicates how effectively the buses are being used. As shown in the graph, the utilization generally decreases as more buses are added. The highest utilization is observed with a single bus, with a utilization rate of 2.476, and the lowest with four buses at 2.257. This suggests that increasing the number of buses does not proportionally increase the number of riders, indicating a saturation point in demand.

The average number of riders on the bus 3.8 at any given time further underscores the underutilization issue. The closest scenario to optimal ridership is observed with one bus having an average of 0.163 riders at a time. The addition of more buses does not significantly increase the number of riders, with the average number of riders decreasing as more buses are added.

The average wait time, as shown in 3.8, at stops varies significantly with the number of buses. With one bus, the average wait time is 54.163 minutes, which decreases as more buses

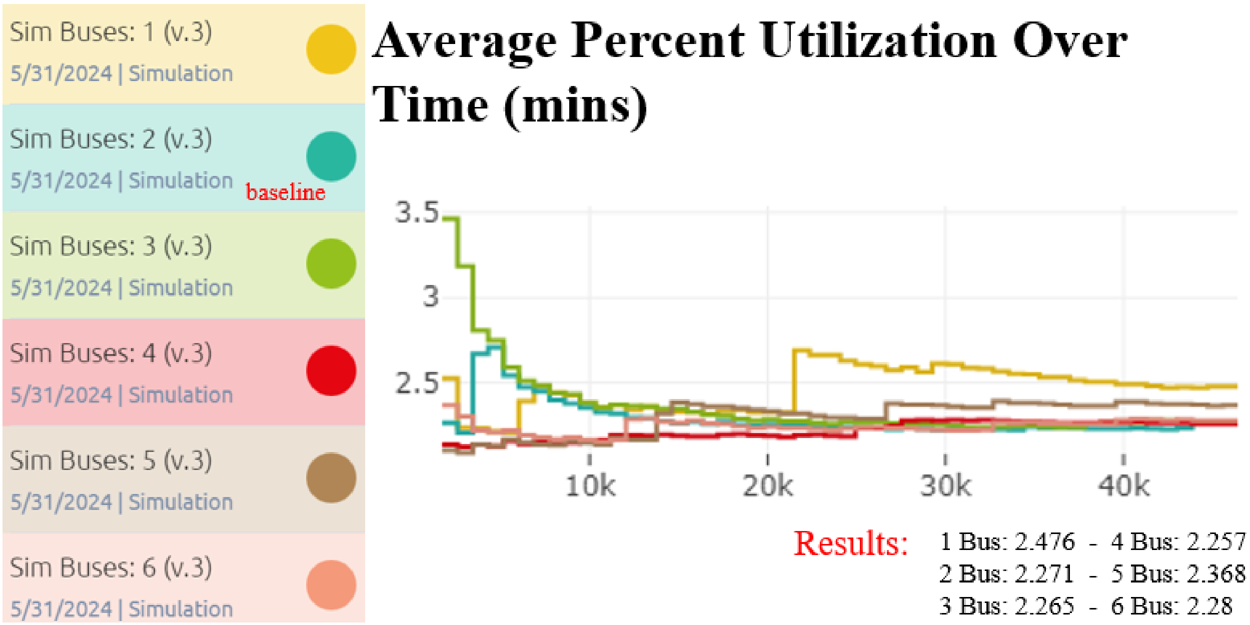

Figure 3.7: Average utilization of a bus at time

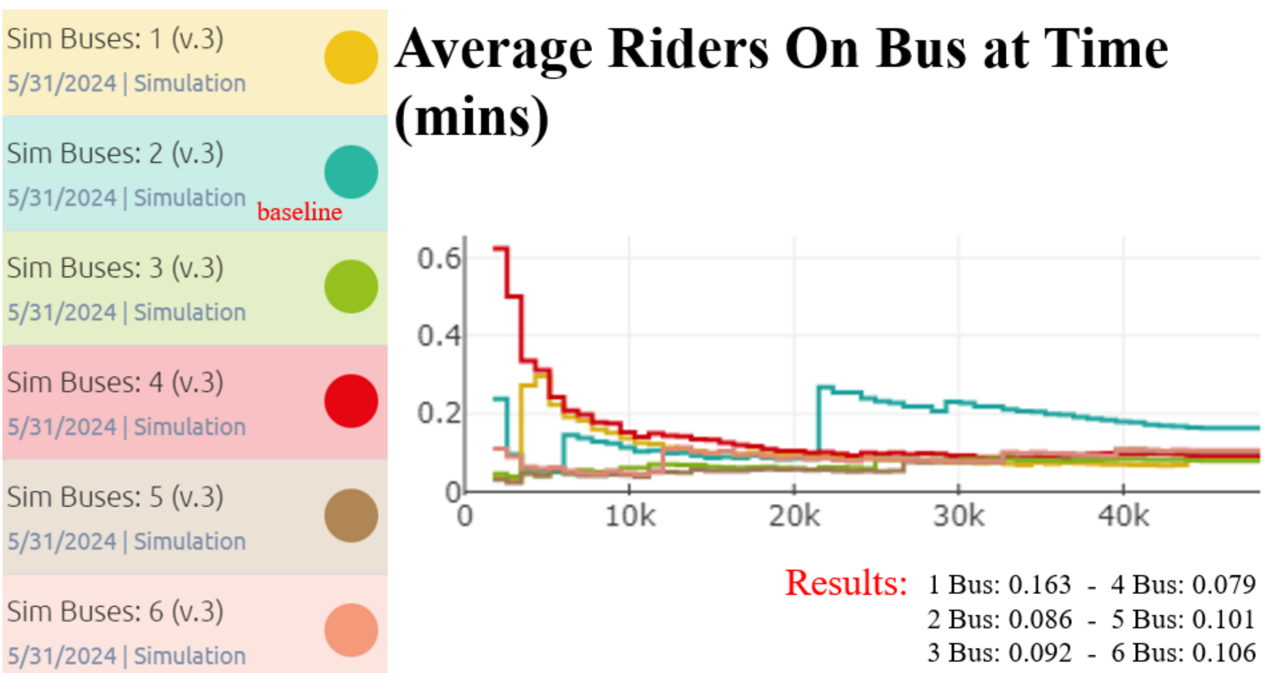

Figure 3.8: Average riders on the bus at a time.

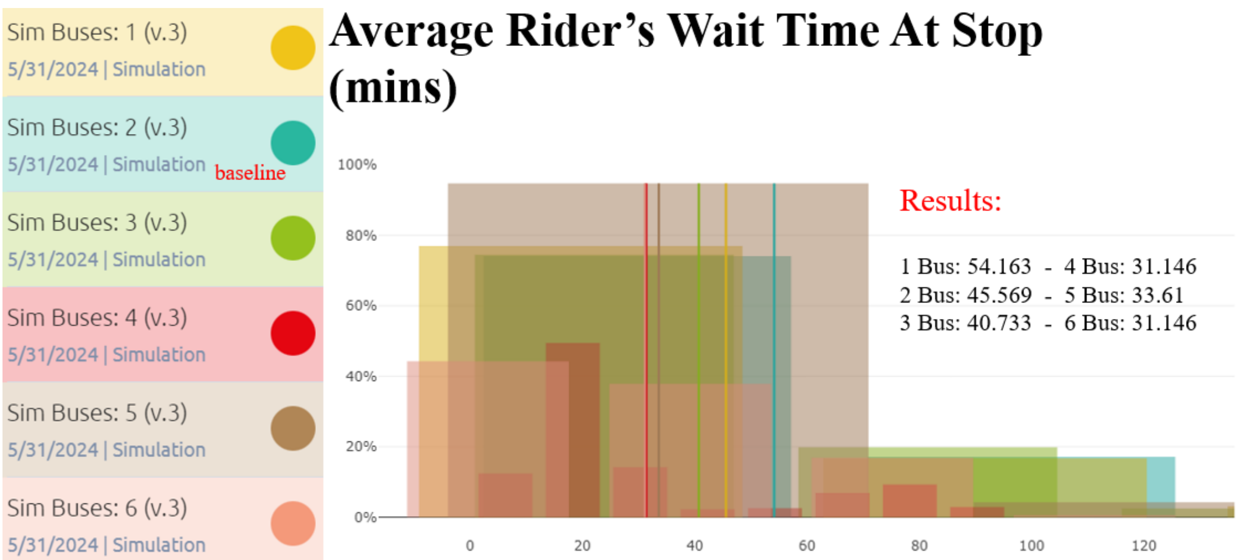

Figure 3.9: Average Waiting Time

are added, reaching the lowest average wait time of 31.146 minutes with four and six buses. This data suggests that adding more buses can significantly reduce wait times, improving the overall efficiency of the system.

The average riding time shows the duration riders spend on the bus. Displayed in 3.8 we can tell the highest average riding time is observed with one bus at 44.552 minutes, which decreases as more buses are added. The lowest average riding time is observed with six buses at 21.301 minutes. This indicates that increasing the number of buses not only reduces wait times but also shortens the time riders spend on the bus. This suggests that increasing the number of buses can improve service utilization, but other factors, such as wait times and route efficiency, also play a crucial role. As seen in 3.11 on the one bus scenario, 64 percent of potential riders balk, while this percentage decreases as more buses are added, reaching 19 percent with five buses. This suggests that increasing the number of buses can improve service utilization, but other factors such as wait times and route efficiency also play a crucial role.

Overall, the simulation results indicate that the KAT system, while efficient in servicing its current users, struggles with underutilization. This issue is exacerbated by the urban sprawl of Knoxville, leading to lower public transport usage than expected. Enhancing the system's appeal and accessibility could potentially increase utilization. While adding more buses can reduce wait times and riding times, a more strategic approach, such as improving route efficiency and marketing, may be necessary to attract more riders and optimize resource use.

From these comparison results, it is evident that the current KAT system is underutilized but not inefficient. To address this, it would be beneficial to create a system that serves those needing public transport without using as many resources as the current KAT bus system. While the utilization of the KAT bus system could be improved through marketing, a more logical solution to save money would be to switch to a system that better suits the community's needs. It is unlikely that the KAT bus system would drastically increase its utilization without significant changes in city planning. Therefore, an uber-like system may be the most suitable option to both save money and serve its constituents effectively.

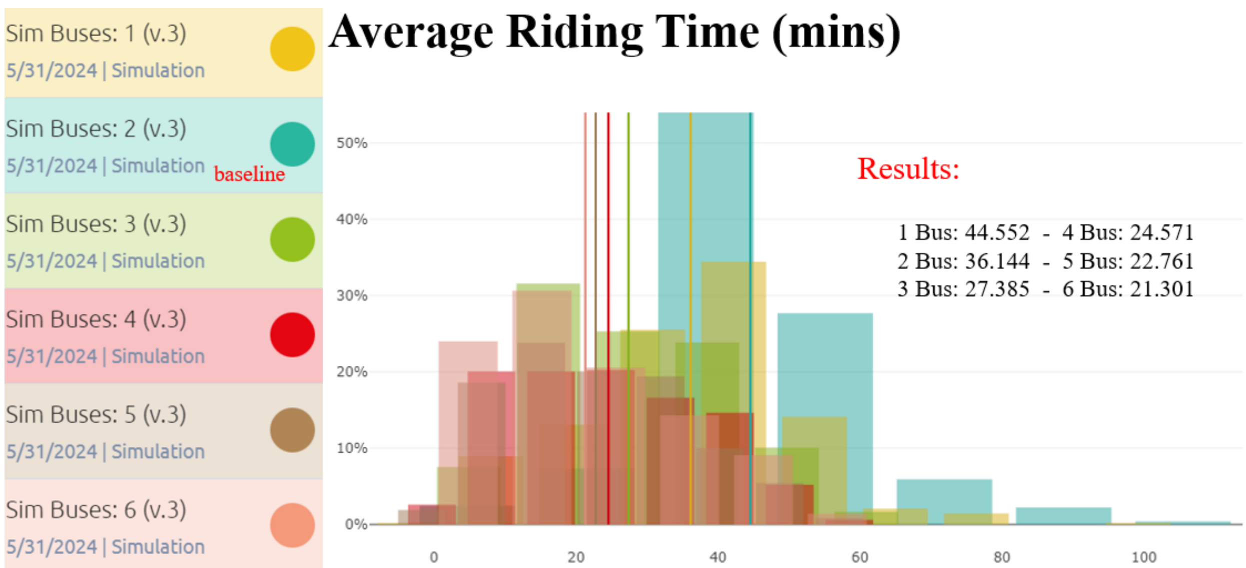

Figure 3.10: Average Riding Time

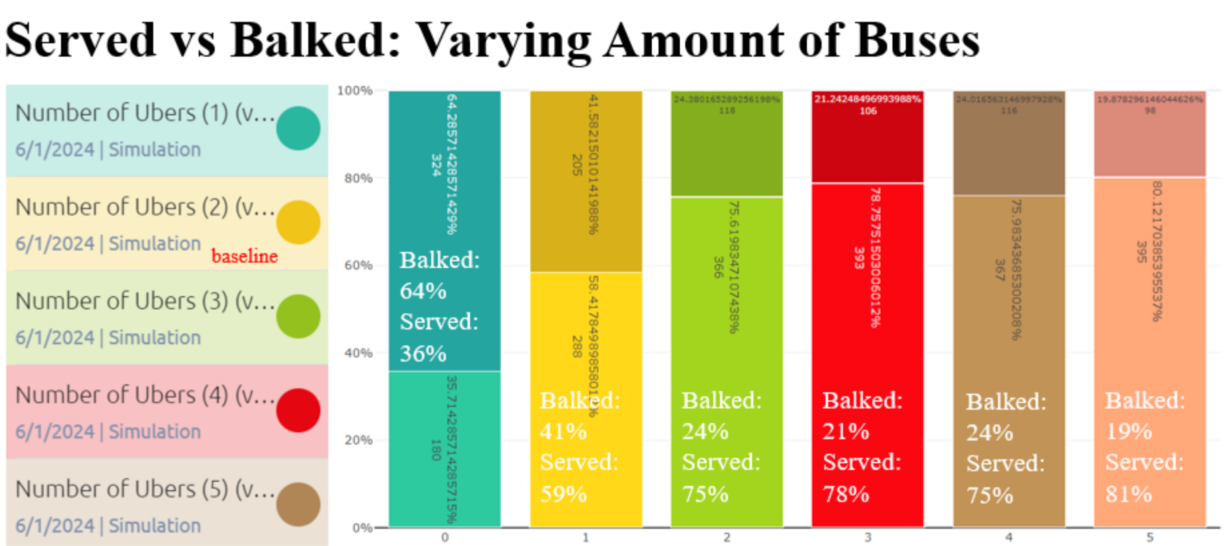

Figure 3.11: Percent of riders Served vs Balked

3.3.2 FIFO Uber Results

The first proposed system to take over the Knoxville public transport system is the First In First Out (FIFO) Uber. The behavior of these users was modeled in AnyLogic and attempted to serve the same area, time period, and constituents as the bus model did. By maintaining a similar model as the bus system, the results of the two can easily be compared, and conclusions about the systems can be drawn.

Baseline

The FIFO model was run based on the baseline parameters presented in table 3.2. The AnyLogic cloud was utilized for ease of access and to gather results from this model. The results of the baseline simulation are presented below.

The wait times and riding times of the baseline FIFO model are presented in figure 3.12. The waiting time graph shows that the average waiting time is just under 9 minutes. This is very similar to the average riding time observed in the bus simulation with similar resources used. Although the waiting times are comparable, the FIFO system proves to have most people waiting less than 15 minutes. The data is slightly skewed due to the number of people that waited up until the balking time of 30 minutes. This indicates that those who were served generally experienced good waiting times. Unlike the bus model, where people had to move to the stops, the FIFO model picks up individuals from their place of residence or where they called the ride, which can be more convenient and time-saving.

The second graph, in figure 3.12 shows the ride time of the users. The average ride time for the FIFO system is around 10 minutes, which is a considerable reduction from the bus baseline of a 40.95 ride time on the bus. An Uber-like system would be expected to have better ride times as they don't have the constant stopping associated with a static bus route. By picking up at the rider's location instead of a stop, we see this system has a better commute time and generally having a better wait time, the FIFO system begins to outshine the bus system. Furthermore, the initial travel requirement of moving to the bus line is eliminated with the FIFO system, making it a more attractive option.

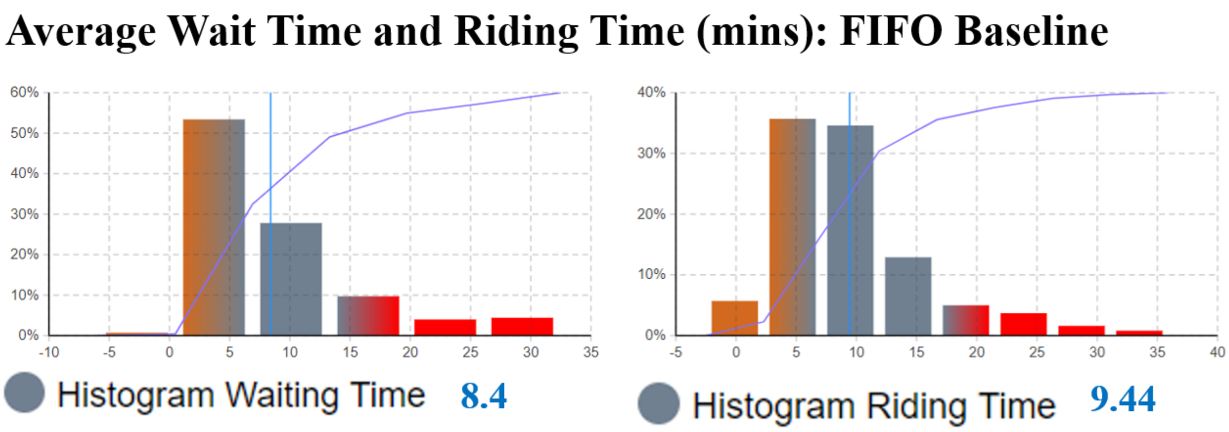

Figure 3.12: Average Waiting time (left) Average Riding time (right)

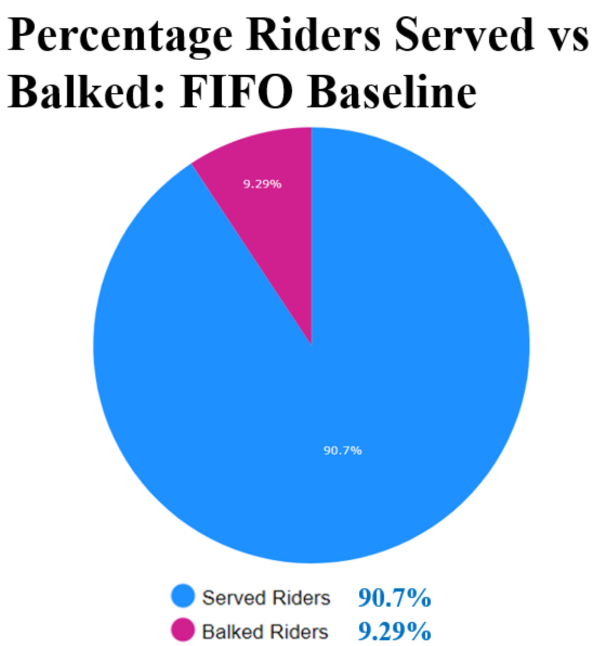

Figure 3.13: Percentage of Riders Balked vs Served

The FIFO (First-In, First-Out) baseline scenario exhibits a balking rate of around 10 percent, significantly outperforming the most optimized bus system with six buses. The six-bus system cannot match the efficiency of two Ubers, which can serve more riders due to their mobility and flexibility. In the bus simulation, the total rider count was reduced because it was unrealistic for a rider to travel from across town. Typically, riders would transfer between bus lines to reach their destinations. Our simulation, however, only included a single line, and having multiple bus lines did not significantly impact wait time, ride time, or utilization.

In figure 3.13, the bus system achieved a maximum service rate of 81 percent, whereas the FIFO Uber model served 90 percent of riders with only a 10 percent balking rate. This suggests that integrating Uber into the public transit system can significantly reduce ride time, wait time, and the percentage of balking riders. Although the FIFO Uber system is not yet optimal, as it completes tasks strictly in FIFO order, it clearly outperforms the traditional bus system.

In summary, the FIFO Uber model offers several advantages over the conventional bus system, including shorter average waiting and riding times and a higher service rate, nearly ten percentage points higher. The bus system's highest service rate was 81 percent, while the FIFO Uber baseline reached almost 90 percent. This indicates potential for further improvement in ensuring all users are served promptly. The comparison underscores the benefits of transitioning to a more flexible and responsive transportation model, such as an Uber-like system, to better meet the needs of Knoxville's population.

Sensitivity Analysis

Since the other main parameters are set up in a way that best reflects the type of system and its relation to the bus system, the only parameter that was chosen to be varied as the number of users in the simulation. The baseline simulation reflects the same amount of resources as the standard bus system, but the question arises of whether fewer can be used to reflect similar or even better results. For this reason, the number of Ubers was varied.

The sensitivity analysis reveals several critical insights into the performance of the FIFO Uber model compared to the traditional bus system. The ride times, as seen in the bottom of

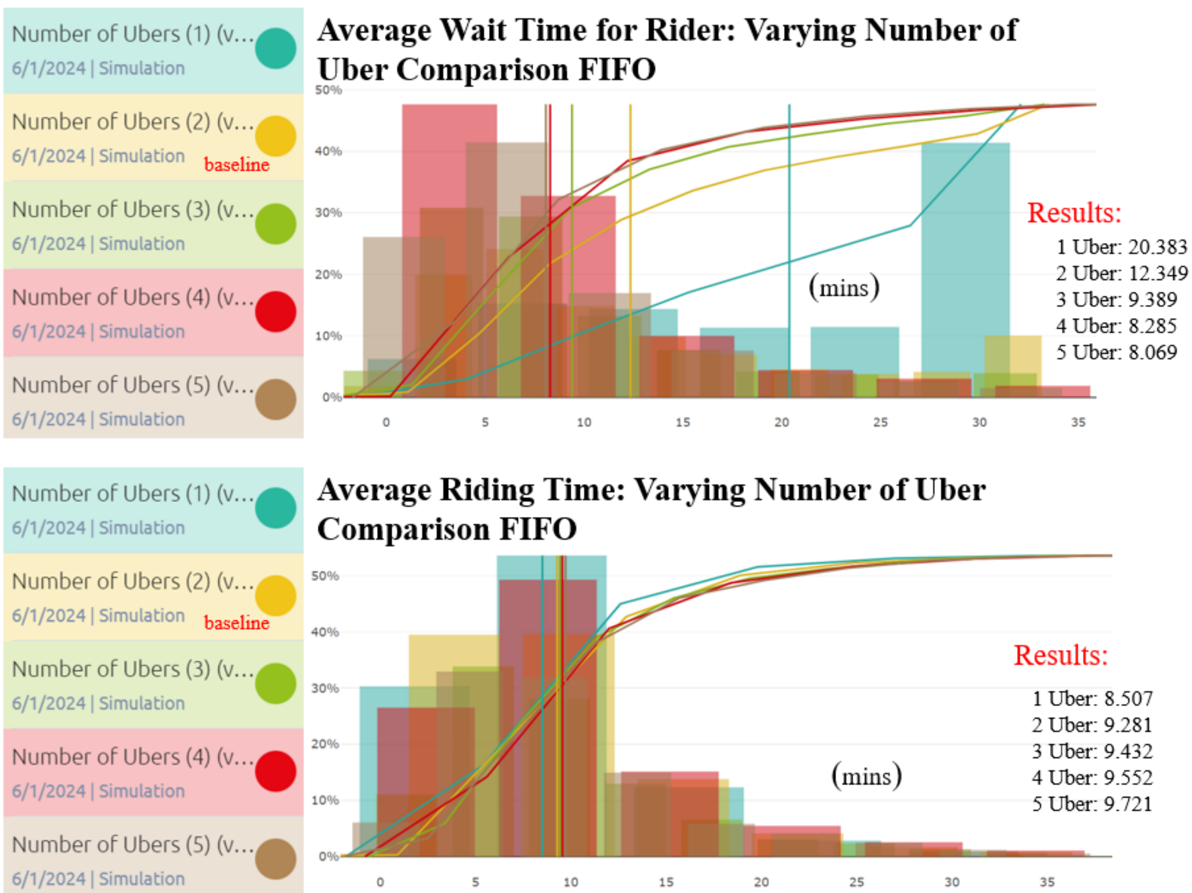

Figure 3.14: Average Wait Time (Top) Average Riding Time (Bottom)

figure 3.14, for different numbers of FIFO Ubers remain relatively constant. This consistency is due to the system serving one request at a time, irrespective of the number of users. As shown in the bottom chart of Figure 3.14, even with the addition of more Uber, the average riding times remain within a narrow range, slightly varying from 8.507 to 9.721 minutes. This is also a very variable time for riders since a car ride will take almost the same time. This marginal increase suggests that the primary focus of adding Ubers should be on reducing wait times rather than impacting ride durations.

Conversely, the top chart in figure 3.14 demonstrates a significant decrease in wait times as the number of Ubers increases. With one Uber, the average wait time is 20.383 minutes, which decreases to 12.349 minutes with two Uber. This trend continues with three, four, and five Ubers, resulting in average wait times of 9.389, 8.285, and 8.069 minutes, respectively. However, adding the sixth Uber does not have a significant impact on the wait time, so it has been left out of the figures. This reduction is intuitive yet essential to quantify; each additional Uber significantly cuts down the wait time, with the most notable decrease occurring when moving from one to two Uber. Adding one more Uber to the baseline cuts around five minutes off the wait time. This indicates that, given sufficient resources, the system's effectiveness could be drastically improved, potentially reducing wait times by half. However, adding a sixth Uber does not show a significant impact, which is why it has been excluded from the figures.

Figure 3.15 shows the different balk rates from the varied Uber experiments. The analysis reveals that five Ubers provide the best results, achieving an almost 100 percent service rate. When increasing the number of Ubers to six, the balk rate remains the same as with five Ubers. This suggests that for a FIFO system handling twenty requests per hour, the optimal number of Ubers is five.

With fewer than three Ubers, the percentage of balking passengers increases significantly. For instance, with one Uber, only 68 percent of riders are served, leaving 32 percent balking. Increasing to two Ubers improves the service rate to 90 percent, with 10 percent balking. Three Ubers further increased the service rate to 96 percent, reducing the balking rate to 4 percent. Four Ubers serve 98 percent of riders, leaving 2 percent balking. Finally, five Ubers achieve a service rate of 99 percent, with only 1 percent of riders balking.

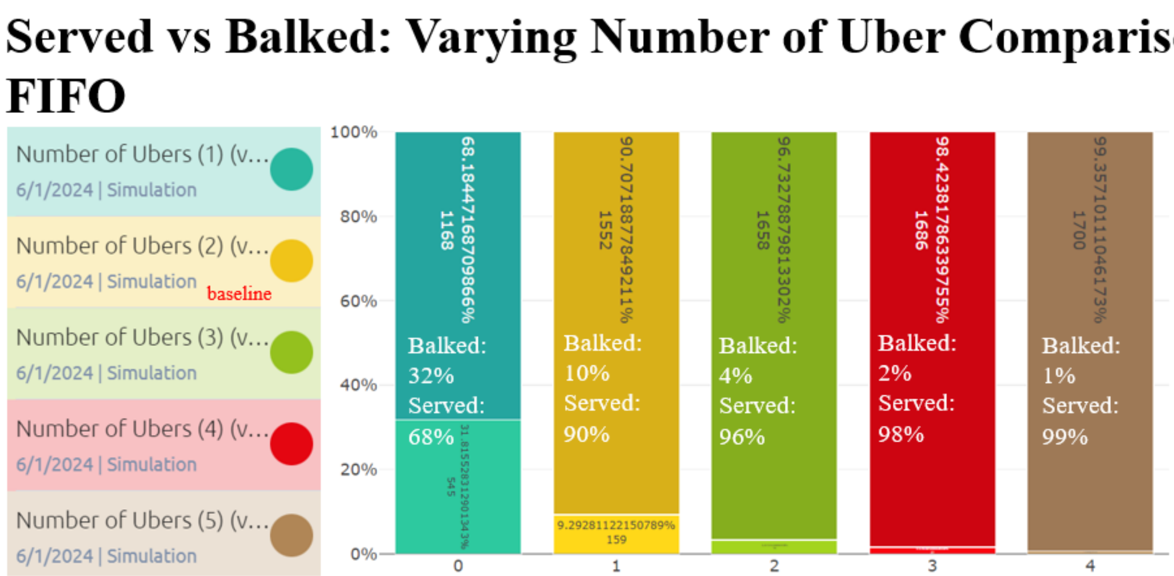

Figure 3.15: Percentage of Riders Balked vs Served

Having only four Ubers leaves 10 of the riders unserved, which is unacceptable for a public transportation system. Public transit should be efficient and accessible, aiming to achieve an almost 100 percent service rate. Thus, based on the results, it can be concluded that for a city like Knoxville, five Ubers is the most optimal number for the FIFO system. Increasing beyond five Ubers does not yield additional benefits, as the balk rate stabilizes, indicating that the system has reached its peak efficiency. Therefore, investing in five Ubers ensures maximum efficiency and customer satisfaction for Knoxville's public transportation needs.

3.3.3 Shared Uber Results

The second system considered for the replacement of the current KAT bus system in Knoxville is the shared Uber system. This system is classified under the dial-a-ride class of public transport. The main difference between the shared and the FIFO Uber systems is that the shared can pick up multiple requests per route, while the FIFO Uber only services one request at a time. The shared Uber simulation was run with the same time and related parameters as the bus simulation, making the comparison between the two easily manageable.

Baseline

The Shared model was run based on the baseline parameters presented in table 3.2. The AnyLogic cloud was utilized for ease of access and to gather results from this model. The results of the baseline shared Uber simulation are presented below.

In figure 3.16, the wait and ride times of the baseline shared Uber system are presented. When examining the wait time graph, it can be observed that the average wait time is below ten minutes after two Ubers, specifically between eight and nine minutes. This is a significant reduction in wait time from both the FIFO and bus systems. This reduction of about seven to eight minutes saves people valuable time and can increase interest in the system. This reduction in time, accompanied by the fact that the user does not need to travel to their pickup location, makes the shared Uber system more attractive than that of the current KAT bus system. Further analysis of the figure shows that almost everyone is

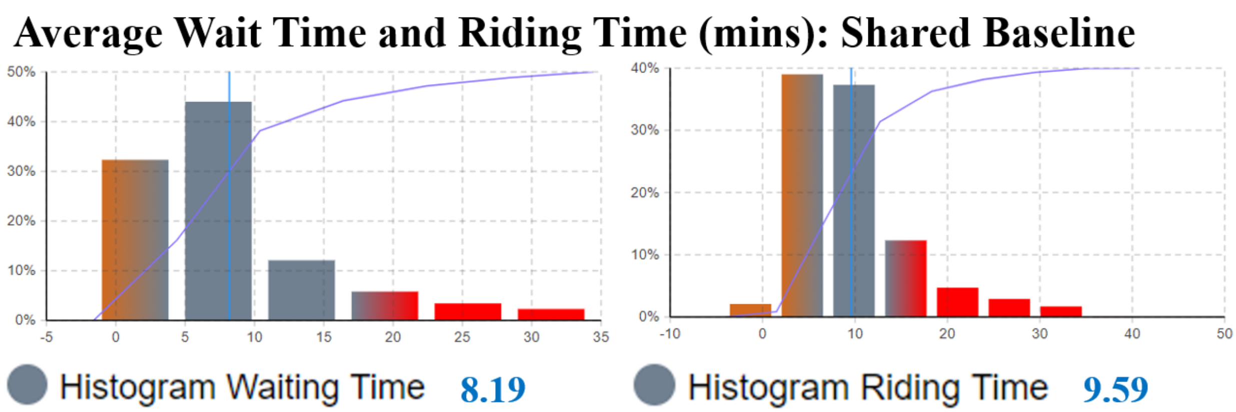

Figure 3.16: Average Waiting time (left) Average Riding time (right)

served in less than ten minutes once three Ubers are added to the system. This means that when a rider calls in a ride, they will, on average, be picked up in 8.19 minutes based on the baseline given. This is not the case in other systems, highlighting another reason the shared Uber system is superior.

The ride time does not change from the FIFO to the shared system. This is an interesting data point because picking up multiple people per route does not majorly influence the amount of time that somebody is in the vehicle. This is also a point to be made about the effectiveness of the system. As the simulation stands, it runs on real data from Knoxville's bus line. This data indicates a large disdain for the current system as most buses will often have a below-one utilization. If the city had more public transit users, the shared system would consequently have a greater impact on the system as a whole.

Looking at 3.15 we can see balking rate of the baseline is 1 percent. This is significantly better than the FIFO Uber system and bus system with the same amount of resources. Based solely on the baseline information, it is clear that the shared Uber system outperforms both the FIFO Uber system and the bus system in terms of the relative metrics.

Sensitivity Analysis

Examining the impact of varying the number of Ubers offers an insightful look into optimizing the shared Uber system in terms of resources used and time efficiency of the users of the system. By analyzing how the number of Ubers in the system affects the different evaluation metrics, it can be further proved why this system outperforms and is a better option for cities similar to Knoxville. A study into the capacity of the Uber was also conducted, but the results were not significant enough to provide actionable insights into the system.

However, the parameter determining if the Uber can have multiple open slots does give some insight into how this variation can be used to advantageously help the system. In figure 3.18 if we take a look at the two histograms, one for waiting and one for riding we can see that the shared does not effect these variables heavily. It does, however, show a slight improvement on the shared vs FIFO by about 4 percent. This indicates that if the system had more utilization, the shared Ubers would consequently have a larger impact.

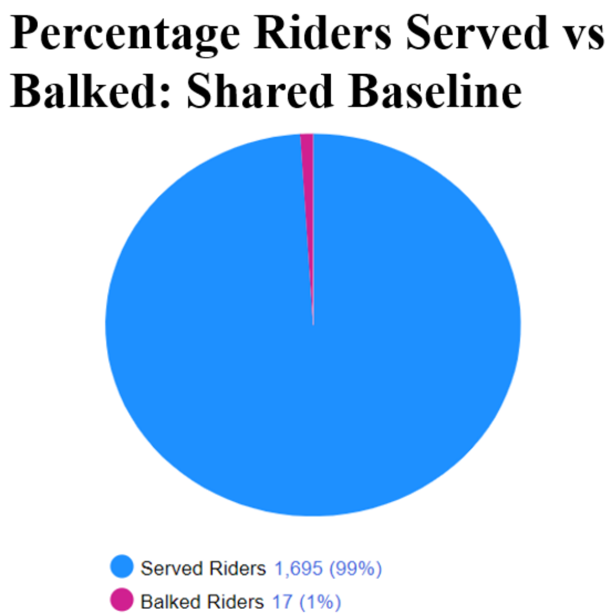

Figure 3.17: Percentage of Riders Balked vs Served

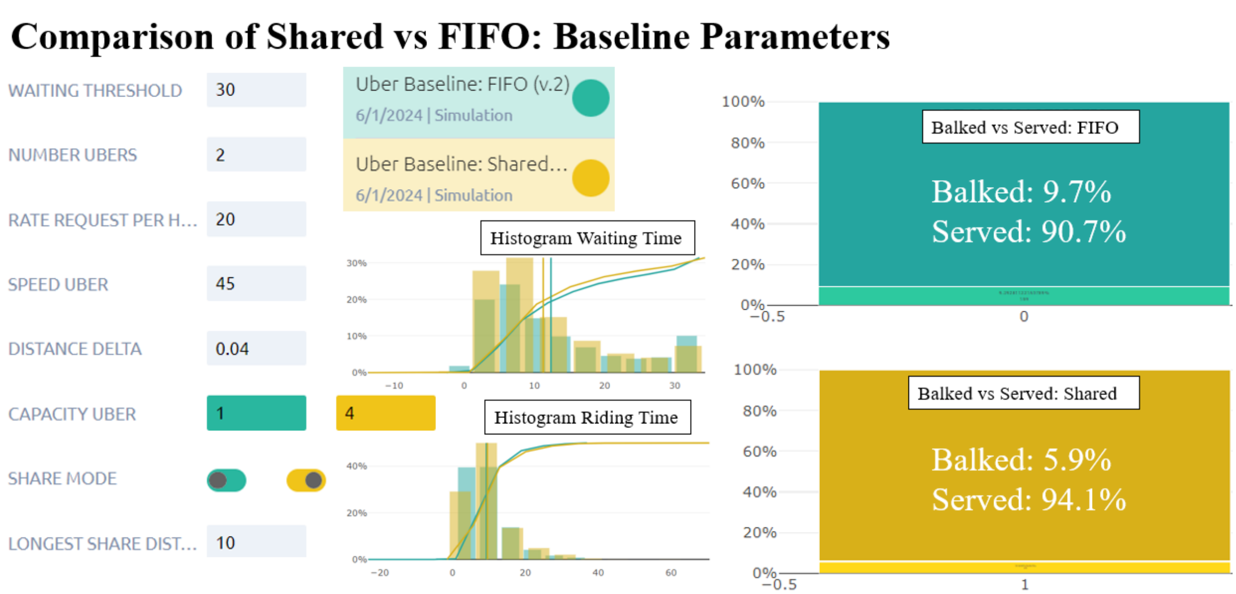

Figure 3.18: Average Waiting Time (top) Average Riding Time (bottom)

The parameter determining whether an Uber can have multiple open slots provides valuable insights into how this variation can be leveraged to enhance the system. As illustrated in figure 3.18, examining the histograms for both waiting and riding times reveals that the shared mode does not significantly impact these variables. However, there is a noticeable improvement in the balked vs. served rates, with the shared mode showing a 4 percent increase in the service rate compared to FIFO.

Specifically, the FIFO mode has a balk rate of 9.7 percent and a service rate of 90.7 percent, whereas the shared mode improves these metrics to a balk rate of 5.9 percent and a service rate of 94.1 percent. This suggests that, under conditions of higher utilization, shared Ubers would likely have an even more substantial positive impact on the system's performance.

In conclusion, while the shared mode does not drastically alter waiting or riding times, it does enhance the overall service rate, making it a valuable consideration for optimizing public transit systems. These findings indicate that implementing shared Ubers can provide a notable improvement in efficiency, especially in scenarios with higher demand. Thus, cities aiming to improve their public transportation systems should consider incorporating shared ride options to maximize resource utilization and service quality.

Figure 3.19 presents the wait and ride times of the different number of Uber experiments. The wait time graph shows that adding more Ubers decreases waiting time. However, having more than five Ubers does not have a significant impact on wait time. Even having five Ubers is not significantly better than four Ubers. Whether the small decrease in the wait time is worth adding an extra Uber would need to be evaluated financially. The ride time is not significantly affected by the number of users present. Based on the wait time and ride time metrics, it can be concluded that the optimal number of Ubers is either four or five, depending on which evaluation is more important to the head of the system, in this case the Department of Transportation in Knoxville.

Figure 3.19 presents the wait and ride times for different numbers of Ubers in shared mode. The wait time graph shows a clear trend: as the number of Ubers increases, the average waiting time decreases. Specifically, with one Uber, the average wait time is 17.541 minutes. This decreases to 11.253 minutes with two Ubers, 9.187 minutes with three Ubers,

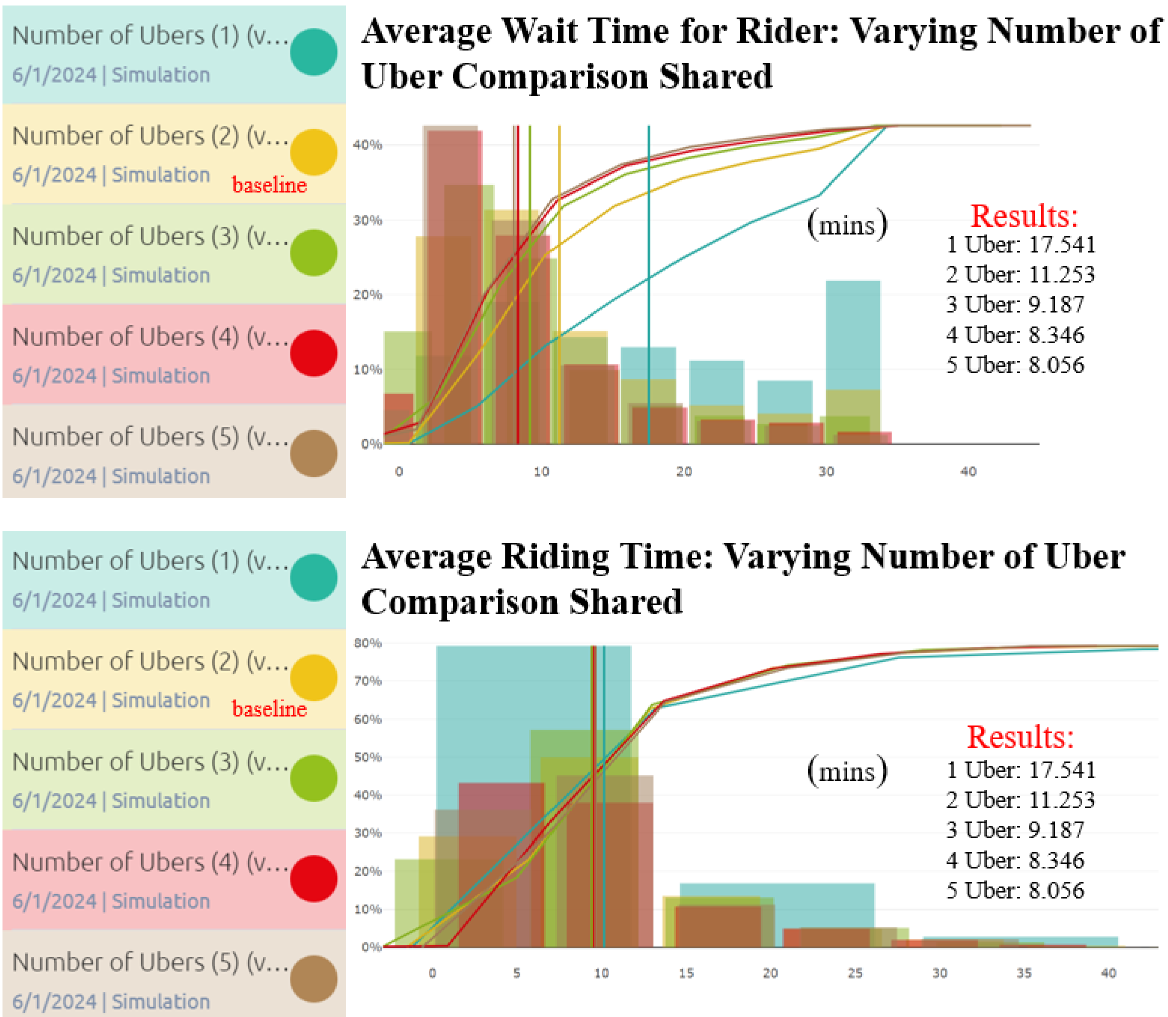

Figure 3.19: Average Waiting Time (top) Average Riding Time (bottom)

8.346 minutes with four Ubers, and 8.056 minutes with five Ubers. Notably, having more than five Ubers does not significantly impact wait times, and the difference between four and five Ubers is minimal. Therefore, whether the slight decrease in wait time justifies the cost of adding an extra Uber requires financial evaluation.

The ride time graph indicates that the average riding time is not significantly affected by the number of Ubers. With one Uber, the ride time is 17.541 minutes, which reduces to 11.253 minutes with two Ubers. For three, four, and five Ubers, the ride times are 9.187, 8.346, and 8.056 minutes, respectively. These values remain relatively stable, suggesting that the addition of more Ubers primarily impacts wait times rather than ride durations.

Based on the metrics of wait time and ride time, it can be concluded that the optimal number of Uber is either four or five. The decision depends on the priorities of the Department of Transportation in Knoxville. If minimizing wait time is the primary goal, then adding a fifth Uber might be considered. However, if cost efficiency is paramount, four Ubers may be the more prudent choice, as the marginal benefit of the fifth Uber is relatively small. This analysis helps in determining the most effective and efficient allocation of resources to enhance public transportation services in Knoxville.

Figure 3.20 illustrates the balking rates for varying numbers of users in the shared mode. The results show a clear improvement in service rates as the number of Ubers increases. With one Uber, the balk rate is 20 percent, with 80 percent of riders being served. This improves significantly with two Ubers, reducing the balk rate to 6 percent and increasing the service rate to 94 percent. With three Ubers, the balk rate further decreases to 3 percent, with a service rate of 97 percent. Four Ubers achieve a balk rate of 2 percent and a service rate of 98 percent, while five Ubers reach an optimal state with only 1 percent balking and 99 percent of riders being served.

The primary concern arises when fewer than four Ubers are deployed, as the balking rates become unacceptably high for a public transportation system. However, with four or more Ubers, the balking rates are negligible, indicating a threshold where the system becomes highly efficient.

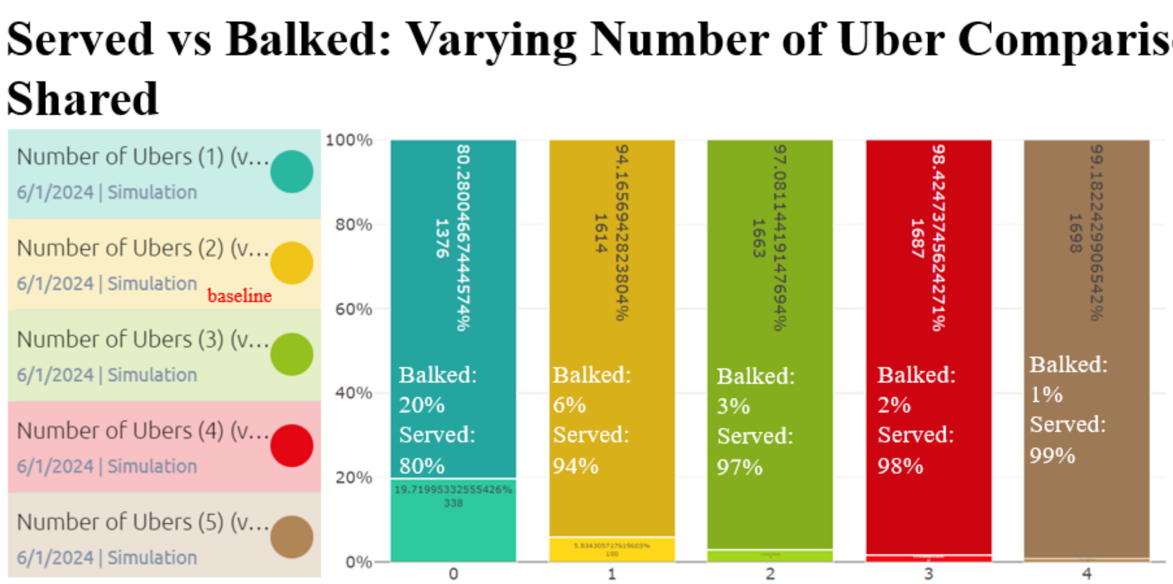

Figure 3.20: Percent of Users Balked or Served

3.3.4 Combined

The final simulation system developed integrates both the shared Uber and bus models. This combined approach allows for a detailed analysis of how these two systems interact and influence each other. Previous findings have indicated that the shared Uber model is highly effective. By incorporating it into the existing bus framework, we can precisely observe the impact of Uber services on a static bus line. This integration not only elucidates the dynamic interplay between the two systems but also highlights potential areas for improvement within the static bus line, offering valuable insights for enhancing overall transit efficiency.

Baseline

In order to effectively evaluate and compare the performance of various transportation parameters within the system, a baseline analysis is essential. This baseline serves as a reference point, providing a standard against which different scenarios and parameters which can be measured. By establishing a comprehensive baseline for both the bus and Uber systems, we can gain a clear understanding of their current efficiency and identify areas for improvement. The following sections present detailed analyses of the average waiting and riding times for both systems, as illustrated in figures 3.21 and 3.22. These baseline metrics will be instrumental in assessing the impact of dynamic demand, service adjustments, and other variables on overall system performance.

The comparative analysis of waiting and riding times for bus and Uber systems, as illustrated in figures 3.21 and 3.22, reveals significant insights into their performance and efficiency. The bus system in figure 3.21 shows an average waiting time of approximately 34.79 minutes, with most riders experiencing waits of up to 40 minutes. In contrast, the Uber system in figure 3.22 offers significantly shorter average wait times of about 17.57 minutes, indicating a more responsive service. Despite these differences in wait times, the average riding times for both systems are similar, with the bus system averaging 31.32 minutes and the Uber system also around 31.32 minutes. This suggests that while Uber provides shorter wait times, the actual travel duration is comparable to that of the bus system.

The histograms for the bus system, in figure 3.21, reveal that waiting times are concentrated around 20-40 minutes, and riding times peak between 20-40 minutes, with most trips completed within 40-60 minutes. The Uber system in figure 3.22, on the other hand, shows a waiting time peak of around 15-20 minutes, with most rides finished within 40 minutes. These findings highlight the need for the bus system to improve its waiting times to remain competitive with ride-sharing services like Uber. Enhancing bus frequency and reducing waiting times could significantly increase rider satisfaction and system efficiency.

Overall, the data underscores the importance of managing and reducing wait times to maintain and increase public transit usage. While Uber's shorter wait times make it a more attractive option for riders prioritizing overall journey time, the bus system has the potential to improve by optimizing schedules. This integrated approach, leveraging the strengths of both traditional and ride-sharing services, can provide a balanced and efficient public transportation system.

The histogram, in figure 3.23, illustrates the average total number of riders on a bus at any given time, showing a significant increase in bus ridership compared to previous static line averages. The current average number of riders per hour per bus has risen to 4.98, a marked improvement from the earlier average of 1.32 riders per hour per bus. The histogram reveals a concentration of bus riders, with peaks observed at 2, 4, and 6 riders, while the cumulative distribution curve indicates that most buses have up to 6 riders at any given time. This increase in ridership is consistent across different intervals, suggesting a more uniformly distributed usage of the bus service throughout the day.

The significant rise in the average number of riders on the bus, now at 4.98 riders per hour, reflects higher demand for the bus service, which can be attributed to several factors, such as improved service frequency, better route optimization, and integrated demand management with the Uber system. The integration of the bus and Uber systems has likely enhanced the overall efficiency and attractiveness of the bus service. Contributing factors to this increase may include reduced wait times, improved service reliability, and the dynamic management of demand by redirecting Uber riders to the bus system when necessary.

This combined approach creates a more balanced and responsive transit network, encouraging greater use of public transportation and resulting in higher ridership levels.

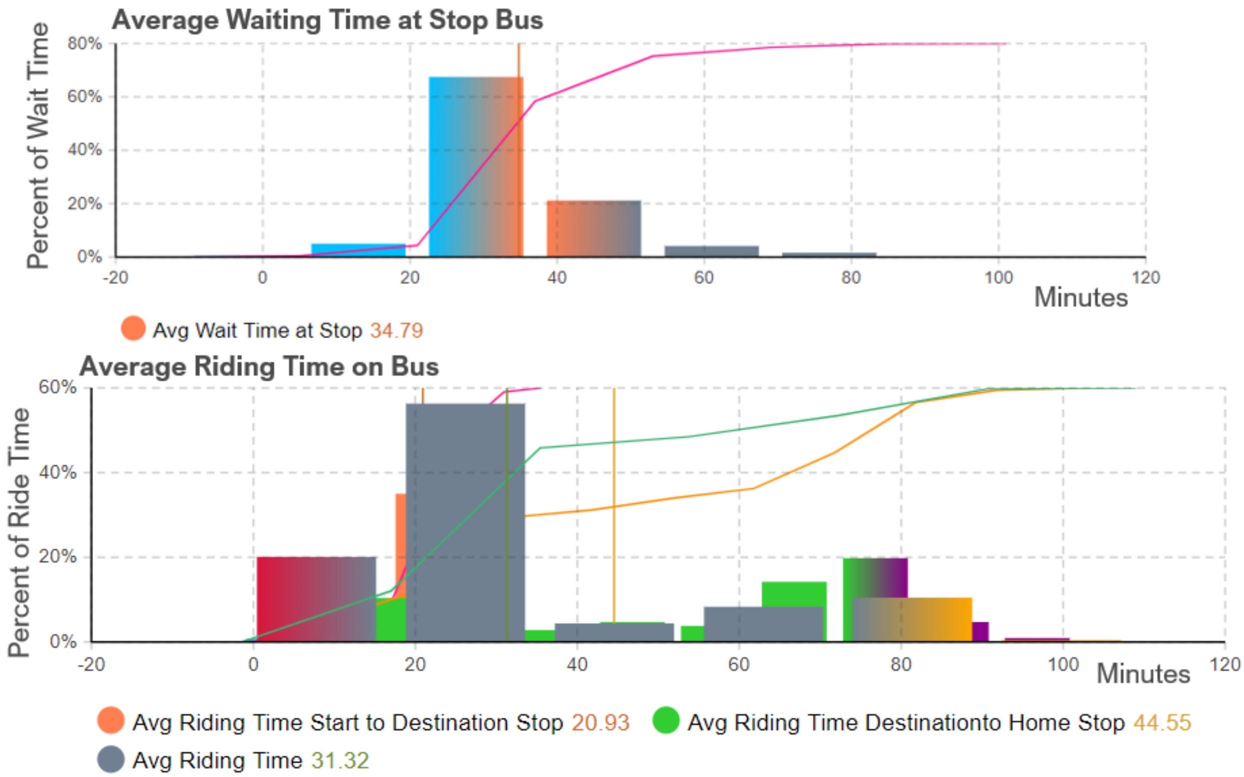

Figure 3.21: Histogram of Riders Average Waiting and Ride Time on Bus.

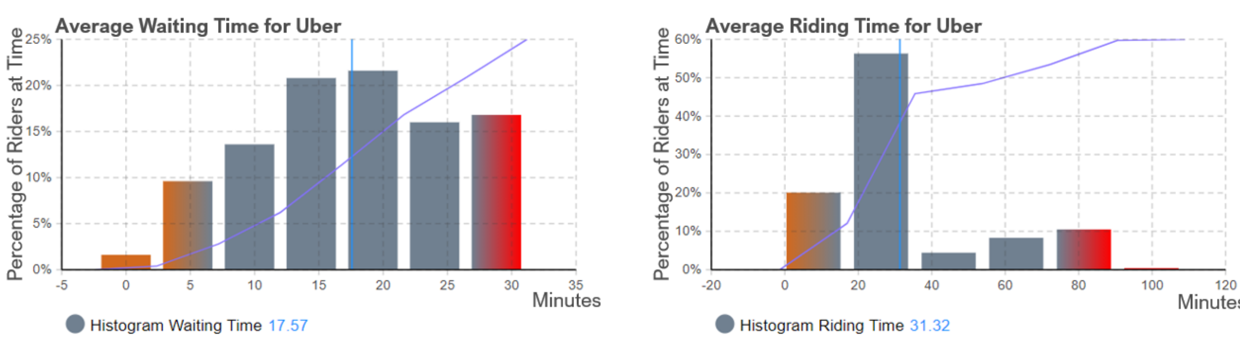

Figure 3.22: Histogram of Riders Average Waiting and Ride Time on Uber.

By leveraging the strengths of both traditional bus services and flexible ride-sharing options, the system can better meet the needs of the population, leading to more efficient and effective public transit solutions.

The pie charts provide a detailed comparative baseline of the percentage of riders served versus those who balked across the combined scenario. This chart is instrumental in understanding the efficiency and capacity of the combined system under varying demand conditions.

In figure 3.13, the static bus baseline, 59 percent of the bus capacity is utilized, while 41 percent remains unutilized. This indicates a relatively balanced system where the majority of riders are served, though there is still a significant portion of unused capacity. This scenario reflects the real-life conditions for the bus system, demonstrating that having two buses per line is the most efficient configuration.

In the shared Uber baseline shown in figure 3.17, an impressive 99 percent of riders are served, with only 1 percent balking. This indicates that the Uber service is highly efficient in handling its designated demand under baseline conditions. The low balk rate suggests that, when operating independently, the Uber system has sufficient capacity to meet rider demand effectively.

The combined baseline in figure 3.24 presents a more complex scenario. The pie charts indicate that only 51 percent of bus riders and 51 percent of Uber riders are served, with 49 percent balking in both cases. This substantial increase in the balk rate, compared to the static bus baseline, can be attributed to the higher demand introduced by combining the two systems. The integrated model increases the overall load on both the bus and Uber services, leading to a higher percentage of riders who are not served. This underscores the impact of increased demand on the system's capacity and efficiency, showing that neither service can handle the combined load optimally under the current conditions.

Comparing the static bus baseline to the combined baseline highlights the strain that increased demand places on the integrated system. While the static bus baseline maintains a balanced utilization rate, serving the majority of riders, the combined system experiences a significant drop in efficiency, with nearly half of the riders in both services balking. The similarities between the static bus baseline and the bus component of the combined baseline

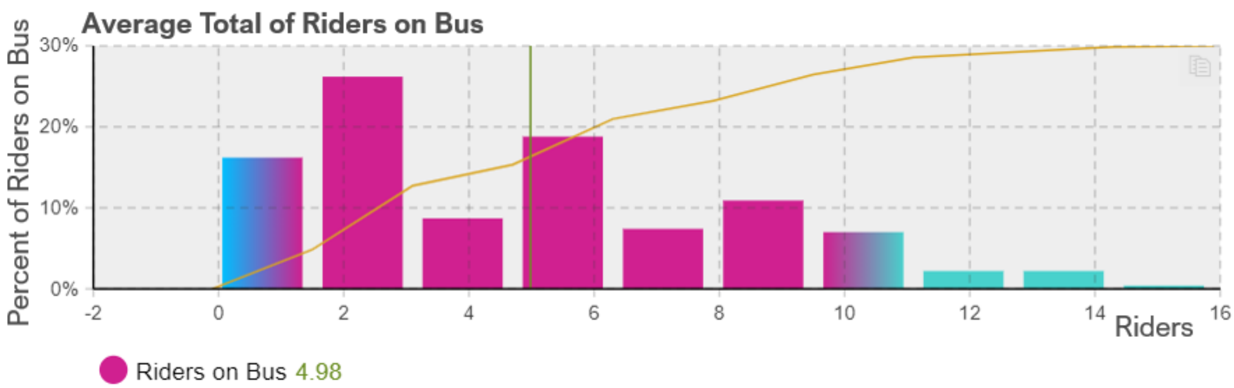

Figure 3.23: Histogram of Average Riders on Bus

are noteworthy. Despite the increased demand in the combined scenario, the bus service's operations do not change significantly, suggesting that the bus system's configuration, with two buses per line, remains optimal for its operation. The primary issue arises from the additional load introduced by integrating the Uber service, which the current bus system cannot adequately absorb.

In conclusion, the poorer performance of the combined baseline underscores the importance of managing demand effectively and ensuring that both services can scale appropriately to handle increased loads. While the bus system operates efficiently under its baseline conditions, integrating it with Uber requires careful consideration of capacity and demand dynamics to maintain high service levels and minimize balking. This analysis highlights the need for strategic adjustments and potential enhancements in infrastructure and resource allocation to better accommodate the combined demand and improve overall system performance.

The time plot in figure 3.25, illustrates the correlation between the average waiting time of Uber riders (red line) and the rate request per hour (yellow line) over a simulation period. This graph offers crucial insights into how rider wait times influence the frequency of ride requests, highlighting the dynamic interplay between service demand and system performance.

Initially, the average waiting time for riders increases sharply, reaching a peak of approximately 15 minutes within the first 100 minutes of the simulation. Correspondingly, the rate request per hour lowers during this period, indicating a high initial demand for Uber services. As the simulation progresses, the average waiting time begins to stabilize, hovering around 20 minutes for the majority of the period from 200 to 1,000 minutes. The rate request had an initial spike, then it levels off at around 20 requests per hour, mirroring the stabilization in waiting times. This parallel movement suggests a direct correlation between the waiting time and the rate of requests: as waiting times decrease or stabilize, the rate of new ride requests also stabilizes, reflecting an equilibrium state in the system where supply meets demand more effectively. This stabilization suggests that the system adjusts to the initial surge in demand.

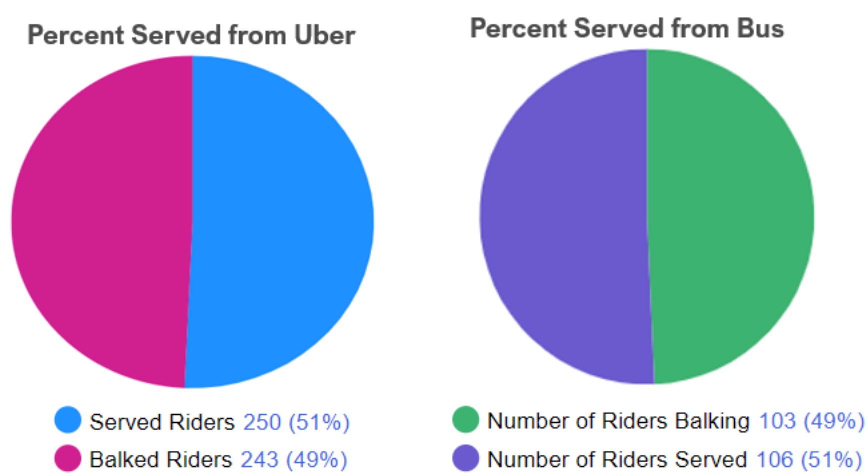

Figure 3.24: Pie Charts of Served vs Balked. Left is the Uber while right is the bus.

The initial high waiting times and request rates can be attributed to a surge in rider demand that the system was initially unprepared to handle efficiently. However, the subsequent stabilization indicates successful system adaptation, through dynamic allocation of resources in response to real-time demand fluctuations.

Overall, this analysis underscores the importance of managing rider wait times to maintain a steady rate of ride requests. By ensuring that waiting times are kept within an acceptable range, the system can sustain a stable demand level, enhancing overall service efficiency and rider satisfaction. This correlation highlights the critical need for responsive and adaptive strategies in ride-sharing services to effectively balance demand and supply, ensuring optimal performance and user experience.

Sensitivity Analysis

Examining the impact of varying the number of Ubers in the combined Uber and bus simulation provides an insightful perspective on optimizing the shared transportation system in terms of resource utilization and time efficiency for users. By analyzing how the number of Ubers in the system affects various evaluation metrics, we can further demonstrate why this integrated approach outperforms and presents a superior option for cities similar to Knoxville. Additionally, a study on the capacity of the Uber vehicles was conducted; however, the results did not yield significant insights into the system's performance, thereby limiting actionable recommendations from this aspect of the analysis.

After analyzing various parameters and metrics, including bus arrival rate and Uber capacity, it was found that these factors did not significantly impact the system's performance. Consequently, our efforts were concentrated on determining the optimal number of Ubers required to enhance the overall efficiency and effectiveness of the combined transportation system. To streamline the analysis and obtain detailed hourly insights, the simulation period was reduced to a single day, thereby making the simulation runs more manageable and less time-consuming.

Given the variable demand based on wait times, it was expected that increasing the number of Ubers would help reduce wait times and increase the number of riders served. The Uber system, characterized by a significantly higher number of riders compared to the

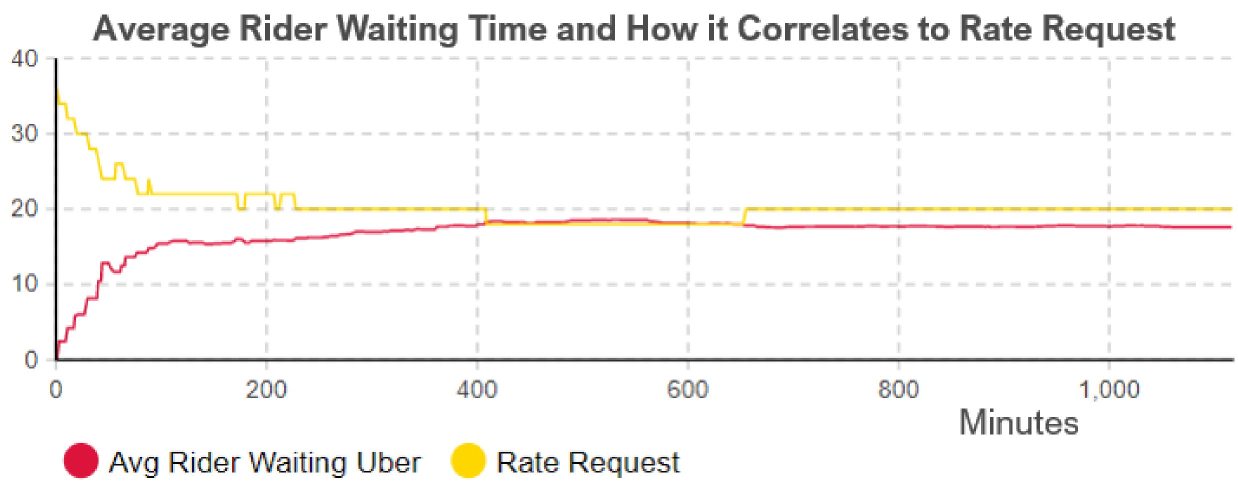

Figure 3.25: Correlation of request rate and rider wait time.

static bus line, underscores the potential benefits of this approach. The static bus line, typically receiving around 70 riders per day, shows even lower ridership in scenarios without injected agents. Since bus usage is relatively sparse, integrating Uber into the system emerges as a promising strategy to boost overall ridership.

Moreover, it is plausible that most new riders would initially opt for the Uber service due to its quicker response times and reduced overall travel duration. This integration would not only attract more users but also improve the public transportation network's overall efficiency. Therefore, focusing on optimizing the number of Ubers in the system is a rational approach to enhancing service quality and meeting rider demand more effectively.

Figure 3.26 illustrates the changes in average waiting time for riders as the number of Ubers in the system is increased from 4 to 7. The histograms and cumulative distribution curves highlight the direct correlation between the number of Ubers and the reduction in waiting time, demonstrating significant improvements in system efficiency.

With 4 Ubers, the average waiting time for riders is approximately 17.57 minutes. The histogram shows a concentration of wait times around the 15-20 minute mark, with a noticeable number of riders experiencing wait times up to 30 minutes. This indicates that while the system can handle the demand to some extent, there is room for improvement to better meet rider expectations and reduce wait times.

Increasing the number of Ubers to 5 results in a reduction of the average waiting time to approximately 16.86 minutes. The histogram displays a similar distribution to that of 4 Ubers, but with a slight shift towards shorter wait times. This suggests that adding more Ubers begins to alleviate some of the demand pressure, making the service more efficient and responsive.

With 6 Ubers, the average waiting time further decreases to around 15.64 minutes. The histogram shows a more pronounced shift towards shorter wait times, with fewer riders experiencing longer waits. This reduction in wait time is a clear indicator that the additional Uber vehicles are effectively absorbing the increased demand, thus improving overall service efficiency.

When the number of Ubers is increased to 7, the average waiting time drops significantly to approximately 14.18 minutes. The histogram illustrates a concentration of wait times around the 10-15 minute range, with very few riders waiting longer than 25 minutes. This substantial reduction in waiting time reflects the high efficiency of the system when adequately equipped with sufficient Uber vehicles.

The addition of Ubers not only reduces wait times but also enhances the overall efficiency of the transportation system. Even with 7 Ubers, the system is capable of moving over 300 more riders in a given day compared to the static bus line scenario. This indicates that the increase in Uber vehicles not only improves individual rider experiences by reducing wait times but also significantly boosts the system's capacity to handle higher volumes of riders efficiently.

The analysis clearly demonstrates that increasing the number of Ubers in the combined transportation system leads to substantial improvements in wait times and overall efficiency. Each additional Uber vehicle contributes to a more responsive and capable service, meeting rider demands more effectively. With 7 Ubers, the system achieves a highly efficient state, minimizing wait times and maximizing the number of riders served. This highlights the importance of optimizing the number of Uber vehicles to ensure a balanced and efficient transportation network that can cater to the needs of a growing urban population.

Extending this analysis to the runs with 8, 9, 10, and 11 Ubers further underscores the trend of improving efficiency with increased Uber vehicles. This is seen in 3.27 with 8 Ubers, the average waiting time drops to approximately 13.52 minutes. The histogram shows a further shift towards shorter wait times, with most riders experiencing wait times below 20 minutes. This continues to indicate the system's ability to effectively manage higher demand with increased Uber availability.

Increasing the number of Ubers to 9 results in an average waiting time of around 12.97 minutes. The histogram distribution demonstrates a majority of wait times clustering around the 10-15 minute range, with very few riders waiting more than 25 minutes. This suggests a significant enhancement in service responsiveness and capacity.

With 10 Ubers, the average waiting time starts to increase to approximately 13.43 minutes. The histogram shows a similar pattern to the 9 Uber scenario, maintaining a concentration of wait times below 20 minutes. This consistency in reduced waiting times indicates a robust capability to handle demand efficiently with 10 Ubers.

Finally, the run with 11 Ubers achieves an average waiting time of around 12.24 minutes. The histogram demonstrates a marked reduction in longer wait times, with most riders waiting under 15 minutes. This represents the most efficient scenario analyzed, but not by much. This is an indication of variable returns.

In summary, as the number of Ubers increases from 4 to 11, there is a consistent and significant reduction in average waiting times, indicating enhanced system efficiency and capacity. Each additional Uber contributes to a more responsive service, effectively managing higher rider volumes and minimizing wait times. Notably, the analysis reveals that once 9 Ubers are introduced, the waiting time begins to level out. Although adding 10 and 11 Ubers further reduces wait times, the improvements are marginal. This suggests that the optimal number of Ubers to handle the varying demand model is 9, as this number provides the most significant benefit without experiencing diminishing returns. This comprehensive analysis underscores the critical importance of optimizing the number of Uber vehicles to ensure a highly efficient and balanced transportation network capable of meeting the demands of a growing urban population.

Figure 3.28 illustrates the percentage of riders served versus those who balked across different scenarios, with varying numbers of Ubers from 4 to 11, and a constant number of 2 buses. Each row of pie charts provides a comparative analysis for a specific number of Ubers, showing the distribution of served and balked riders for both the Uber and bus systems. This analysis demonstrates the impact of increasing the number of Ubers on the efficiency and performance of the combined transportation system.

In the first row, the first two pie charts represent the scenario with 4 Ubers. Here, 51 percent of Uber riders are served while 49 percent balk, indicating that the system is struggling to meet the demand effectively. In the bus system, 51 percent of riders are served, and 49 percent balk, reflecting a similar performance. The high balk rates in both systems suggest that 4 Ubers are insufficient to handle the rider demand efficiently.

The next two pie charts in the first row show the scenario with 5 Ubers. In this case, 68 percent of Uber riders are served, and 32 percent balk, showing a significant improvement in service efficiency compared to the 4 Uber scenario. For the bus system, 66 percent of riders are served, and 34 percent balk. The improved service rates in both the Uber and bus

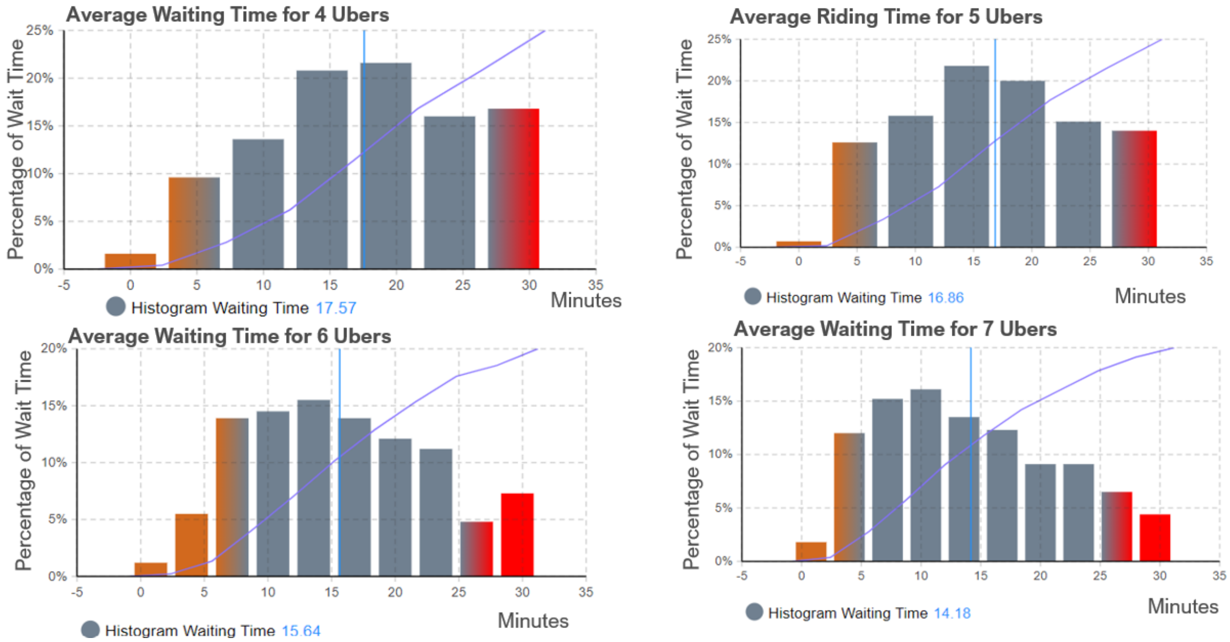

Figure 3.26: Average wait time for 4,5,6, and 7 Ubers respectively.

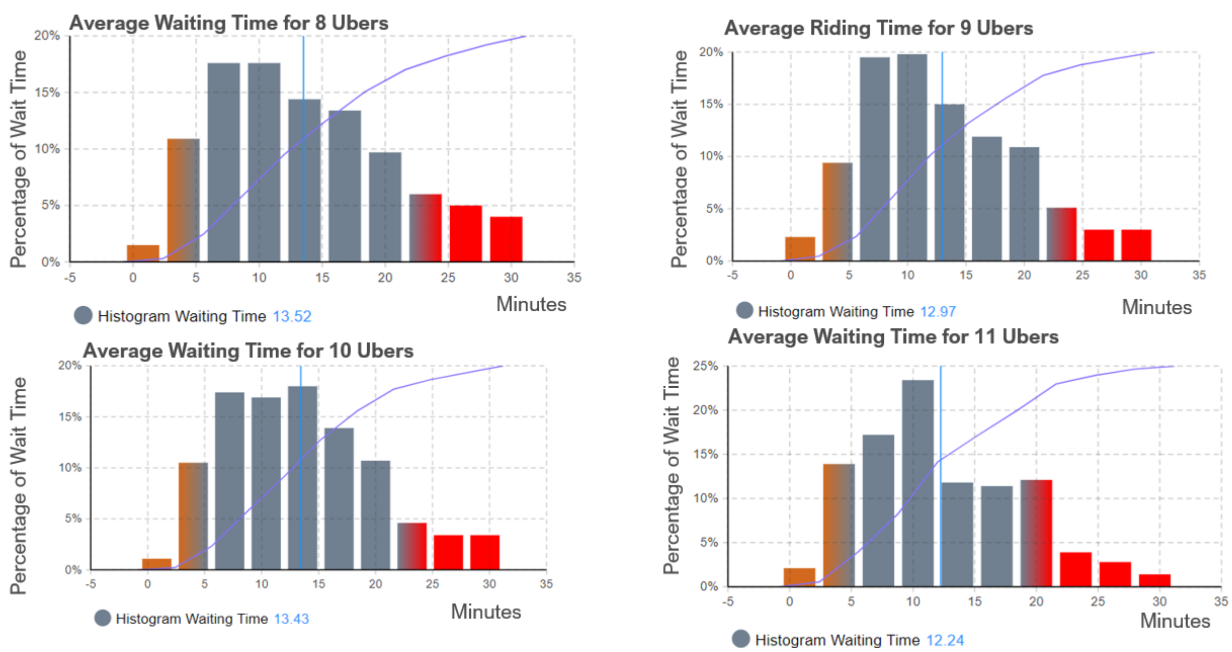

Figure 3.27: Average wait time for 8, 9, 10, and 11 Ubers respectively.

systems indicate that increasing the number of Ubers to 5 enhances the system's ability to meet rider demand more effectively.

In the second row, the first two pie charts represent the scenario with 6 Ubers. Here, the Uber system shows a substantial improvement, with 77 percent of riders served and only 23 percent balking. In the bus system, 64 percent of riders are served, and 36 percent balk. The further reduction in balk rates in the Uber system highlights the positive impact of adding more Ubers, leading to better service efficiency and higher rider satisfaction.

The final two pie charts in the second row illustrate the scenario with 7 Ubers. In this case, the Uber system achieves an impressive 87 percent rider service rate, with only 13 percent balking. The bus system shows 54 percent of riders served and 46 percent balking. The significant improvement in the Uber system's performance with 7 Ubers demonstrates the high efficiency of the system in handling increased rider demand, resulting in minimal balk rates.

Extending this analysis to the runs with 8, 9, 10, and 11 Ubers, shown in figure 3.29, further underscores the trend of improving efficiency with increased Uber vehicles. With 8 Ubers, 88 percent of Uber riders are served while 12 percent balk, showing a continued improvement in service efficiency. For the bus system, 48 percent of riders are served and 52 percent balk, indicating that the bus system still faces challenges in meeting rider demand effectively.

With 9 Ubers, the Uber system serves 92 percent of riders, with only 8 percent balking, highlighting a significant increase in efficiency. The bus system shows 61 percent of riders served and 39 percent balking, reflecting improved performance compared to previous scenarios.

Increasing the number of Ubers to 10 results in 92 percent of Uber riders being served and 8 percent balking. The bus system serves 61 percent of riders, with 39 percent balking, indicating a stabilization in performance improvement.

Finally, with 11 Ubers, the Uber system achieves its highest efficiency, serving 94 percent of riders with only 6 percent balking. The bus system serves 60 percent of riders, with 40 percent balking, showing consistent performance. This demonstrates the rate of return window. We can tell that once we get above 9 Ubers added to the system the rate of return starts to even out.

Overall, this analysis clearly demonstrates that increasing the number of Ubers in the combined transportation system leads to substantial improvements in both the Uber and bus systems. Each additional Uber vehicle contributes to a more responsive and capable service, effectively reducing the number of balked riders and increasing the overall number of served riders. With 9 Ubers, the system begins to see a leveling out of waiting times, indicating an optimal solution where further additions result in diminishing returns. However, the efficiency and increased rider capacity with more Ubers underscore the system's ability to adapt to varying demand levels, providing a robust solution for urban transit challenges. This highlights the importance of optimizing the number of Uber vehicles to ensure a balanced and efficient transportation network that can cater to the needs of a growing urban population.

The series of pie charts in figure 3.30 illustrate the service efficiency of the combined Uber and bus system across varying numbers of Ubers, ranging from 4 to 11. This visual representation allows us to analyze the system's performance in terms of the percentage of riders served versus those who balked, offering insights into the impact of increasing Uber availability on overall service efficiency.

The initial scenario with 4 Ubers reveals significant service challenges, with nearly half of the riders balking due to insufficient Uber availability. This indicates that at this level, the system struggles to meet demand effectively, resulting in high balk rates and low service satisfaction. As we increase the number of Ubers to 5, there is a noticeable improvement in service rates, reflecting the system's enhanced capacity to manage demand more efficiently. This improvement continues with the addition of more Ubers.

The scenarios with 6 and 7 Ubers show substantial gains in service efficiency, with a marked reduction in the percentage of balked riders. The system becomes increasingly capable of meeting rider demand, providing more reliable and timely service. The jump from 6 to 7 Ubers demonstrates a significant decrease in balk rates, indicating a critical threshold where the system starts to handle demand more robustly.

When the number of Ubers is increased to 8 and 9, the system approaches optimal efficiency, with a high percentage of riders being served and minimal balking. These

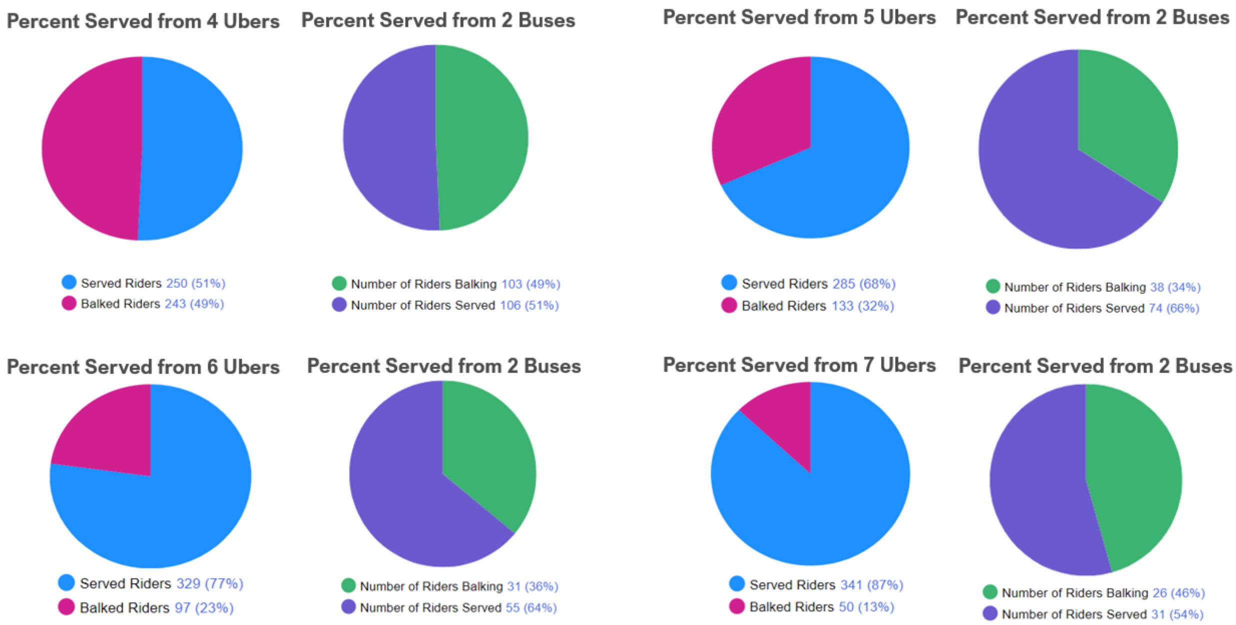

Figure 3.28: Balked vs Served for 4,5,6, and 7 Ubers respectively.

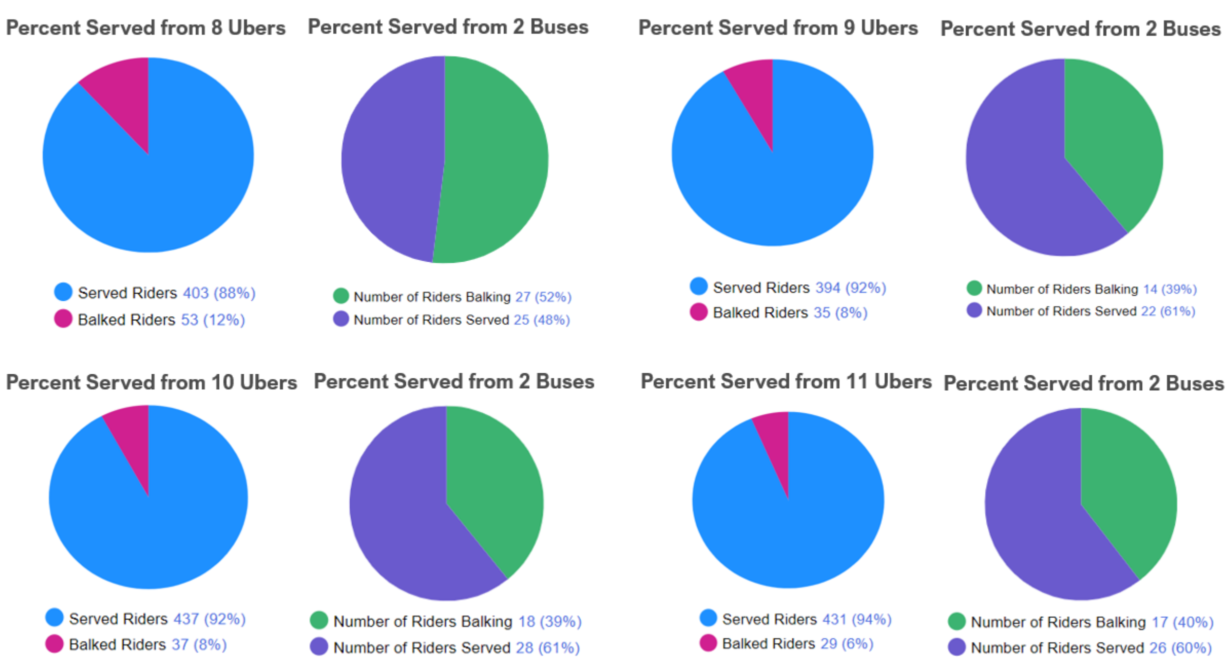

Figure 3.29: Balked vs Served for 8, 9, 10, and 11 Ubers respectively.

scenarios underscore the system's ability to manage high demand effectively, showcasing a well-balanced transportation network that maximizes rider satisfaction and minimizes wait times. The addition of 10 and 11 Ubers continues to show improvements, but the gains begin to plateau, suggesting diminishing returns with each additional Uber beyond this point.

The overall analysis indicates that while increasing the number of Ubers significantly improves service efficiency, there is a point at which additional Ubers yield marginal benefits. Specifically, the scenarios with 8 to 10 Ubers present the best balance between resource allocation and service efficiency, minimizing balk rates and maximizing rider satisfaction. Beyond 10 Ubers, the incremental benefits decrease, suggesting that the optimal number of Ubers for this system lies between 8 and 10.

In conclusion, the best option for optimizing the combined Uber and bus system is to maintain a fleet of approximately 9 to 10 Ubers. This range provides the most significant improvements in service efficiency without incurring unnecessary resource allocation, ensuring a balanced and effective transportation network capable of meeting the demands of a growing urban population.

3.3.5 Conclusion

After thorough analysis and evaluation of different transportation systems using the AnyLogic model developed for the case study of Knoxville, it is clear that the combined Uber and bus system, particularly with 9 Ubers, offers the optimal solution for enhancing public transportation efficiency and rider satisfaction.

The traditional bus model, while efficient in certain aspects, struggles with low utilization and higher wait times. The sensitivity analysis demonstrated that even with increased bus numbers, the improvement in service utilization was marginal, and the system remained underutilized. The urban sprawl of Knoxville exacerbates this issue, making it clear that the current KAT bus system does not adequately meet the needs of its constituents.

The FIFO Uber model showed significant improvements over the bus system, with reduced wait and ride times, and a higher service rate. The sensitivity analysis revealed that adding Ubers to the system consistently improved efficiency, with the optimal number of Ubers being five for the FIFO system. However, while this system outperformed the

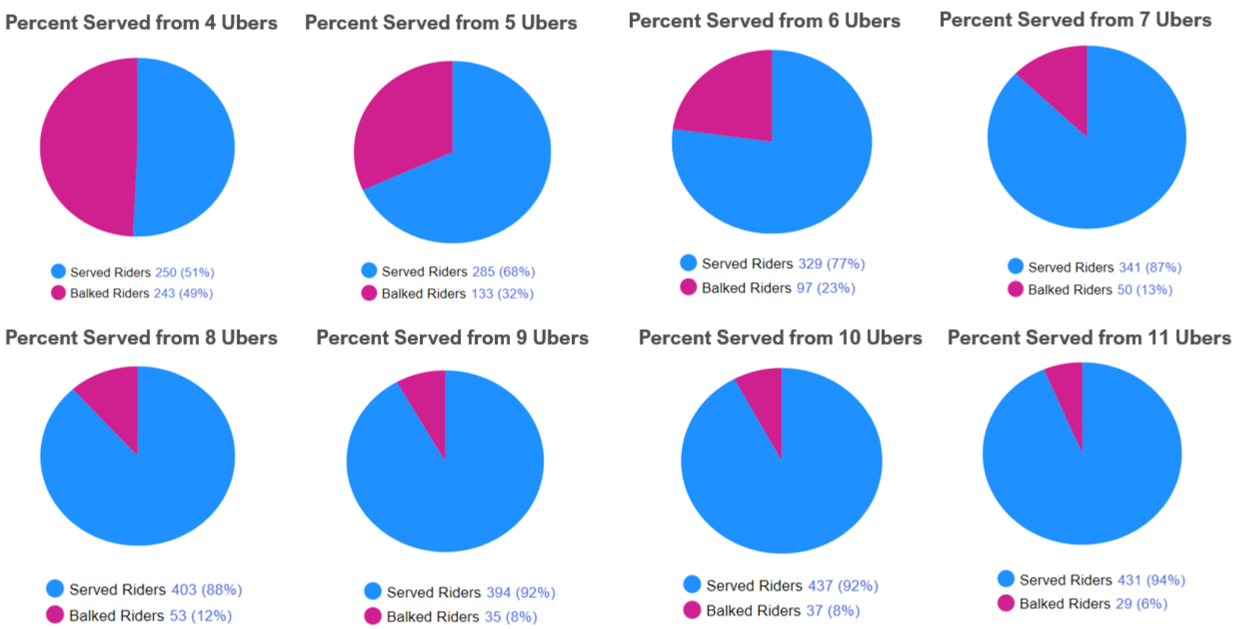

Figure 3.30: Balked vs Served for all scenarios of the Uber.

bus model, it still did not reach the highest levels of efficiency observed in the shared Uber system.

The shared Uber model further improved upon the FIFO system, offering even shorter wait times and a higher percentage of riders served. The sensitivity analysis indicated that having four or five Ubers provided the best balance between resource allocation and service efficiency, significantly reducing balk rates and increasing rider satisfaction.

The combined Uber and bus system emerged as the most effective solution. The integration of shared Uber services with the existing bus framework allowed for a more dynamic and responsive transportation network. The combined system showed substantial improvements in wait times, ride times, and service rates compared to the standalone bus or Uber models. The analysis demonstrated that increasing the number of Ubers in the combined system led to consistent and significant reductions in wait times and balk rates.

Notably, the analysis of scenarios with 4 to 11 Ubers revealed that the optimal number of Ubers for the combined system is 9. This configuration provided the best balance between resource allocation and service efficiency, minimizing wait times and maximizing the number of riders served. Beyond 9 Ubers, the incremental benefits diminished, indicating a point of diminishing returns.

In conclusion, the combined Uber and bus system with 9 Ubers is the best scenario for optimizing public transportation in Knoxville. This system effectively balances the strengths of both traditional bus services and flexible ride-sharing options, providing a highly efficient and responsive transportation network that meets the needs of a growing urban population. By implementing this combined approach, Knoxville can enhance rider satisfaction, reduce wait times, and increase the overall efficiency and capacity of its public transportation system.

Bibliography

[1] Abdallah, T. (2023). Sustainable mass transit: Challenges and opportunities in urban public transportation. 4

[2] Al-Abbasi, A. O., Ghosh, A., and Aggarwal, V. (2019). Deeppool: Distributed model-free algorithm for ride-sharing using deep reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, 20(12):4714–4727. 12

[3] Almahasneh, R., Tüű-Szabó, B., Kóczy, L. T., and Földesi, P. (2020). Optimization of the time-dependent traveling salesman problem using interval-valued intuitionistic fuzzy sets. *Axioms*, 9(2):53. 16, 17

[4] Almquist, Z. W. (2010). Us census spatial and demographic data in r: the uscensus2000 suite of packages. *Journal of Statistical Software*, 37:1–31. 13

[5] Anderson, M. (2016). Who relies on public transit in the u.s. 7

[6] Attajer, A., Darmoul, S., Chaabane, S., Riane, F., and Sallez, Y. (2021). Benchmarking simulation software capabilities against distributed control requirements: Flexsim vs anylogic. In *Service Oriented, Holonic and Multi-agent Manufacturing Systems for Industry of the Future: Proceedings of SOHOMA 2020*, pages 520–531. Springer. 2

[7] Attoh, K. A. (2014). What type of public transit for what type of public? In *New Labor Forum*, volume 23, pages 58–66. SAGE Publications Sage CA: Los Angeles, CA. 11

[8] Attoh, K. A. (2019). *Rights in Transit: Public Transportation and the Right to the City in California's East Bay*. University of Georgia Press. 5, 6

[9] Avila-Palencia, I., Panis, L. I., Dons, E., Gaupp-Berghausen, M., Raser, E., Götschi, T., Gerike, R., Brand, C., De Nazelle, A., Orjuela, J. P., et al. (2018). The effects of transport mode use on self-perceived health, mental health, and social contact measures: a cross-sectional and longitudinal study. *Environment international*, 120:199–206. 8, 9

[10] Baek, D. (2016). The effect of public transportation accessibility on food insecurity. *Eastern economic journal*, 42:104–134. 7

[11] Barkenbus, J., Menard, R. J., English, B. C., and Jensen, K. L. (2006). Resource and employment impact of a renewable portfolio standard in the tennessee valley authority region. *University of Tennessee*. 4

[12] Basu, S. (2012). Tabu search implementation on traveling salesman problem and its variations: a literature survey. 21

[13] Beirão, G. and Cabral, J. S. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport policy*, 14(6):478–489. 1

[14] Bianchessi, N. and Righini, G. (2007). Heuristic algorithms for the vehicle routing problem with simultaneous pick-up and delivery. *Computers & Operations Research*, 34(2):578–594. 17

[15] Billheimer, J., Lave, R. E., Jones, P., Fratessa, C., Newman, D., Holoszyc, M., Fondahl, G., et al. (1979). Paratransit handbook: A guide to paratransit implementation: Volume i-parts 1-3. Technical report, United States. Urban Mass Transportation Administration. 10

[16] Bolten, N., Amini, A., Hao, Y., Ravichandran, V., Stephens, A., and Caspi, A. (2015). Urban sidewalks: visualization and routing for individuals with limited mobility. In *Proceedings of the 1st International ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics*, pages 122–125. 5

[17] Branke, J. and Guntsch, M. (2004). Solving the probabilistic tsp with ant colony optimization. *Journal of Mathematical Modelling and Algorithms*, 3:403–425. 21

[18] Bureau, U. C. (2024). United states census bureau. 61

[19] Campbell, A. M. and Savelsbergh, M. (2004). Efficient insertion heuristics for vehicle routing and scheduling problems. *Transportation science*, 38(3):369–378. 19

[20] CARTA (2023). Charleston area regional transportation authority. 61

[21] Ceder, A. (2002). A step function for improving transit operations planning using fixed and variable scheduling. In *Transportation and Traffic Theory in the 21st Century*, pages 1–21. Emerald Group Publishing Limited. 12

[22] Chandakas, E. (2020). On demand forecasting of demand-responsive paratransit services with prior reservations. *Transportation Research Part C: Emerging Technologies*, 120:102817. 10

[23] Cheikhrouhou, O. and Khoufi, I. (2021). A comprehensive survey on the multiple traveling salesman problem: Applications, approaches and taxonomy. *Computer Science Review*, 40:100369. 16

[24] Chen, W., Petitti, D. B., and Enger, S. (2004). Limitations and potential uses of census-based data on ethnicity in a diverse community. *Annals of epidemiology*, 14(5):339–345. 25

[25] Colorni, A. and Righini, G. (2001). Modeling and optimizing dynamic dial-a-ride problems. *International transactions in operational research*, 8(2):155–166. 11, 14, 15

[26] Cordeau, J.-F. and Laporte, G. (2007). The dial-a-ride problem: models and algorithms. *Annals of operations research*, 153:29–46. 17

[27] DCTA (2023). Denton county transportation authority. 61

[28] Desale, S., Rasool, A., Andhale, S., and Rane, P. (2015). Heuristic and meta-heuristic algorithms and their relevance to the real world: a survey. *Int. J. Comput. Eng. Res. Trends*, 351(5):2349–7084. 20

[29] Dethloff, J. (2002). Relation between vehicle routing problems: an insertion heuristic for the vehicle routing problem with simultaneous delivery and pick-up applied to the vehicle routing problem with backhauls. *Journal of the Operational Research Society*, 53(1):115–118. 19

[30] Ducre, G. (2022). Special needs man with five jobs losing his primary source of transportation. 5, 6

[31] Dutko, P., Ver Ploeg, M., and Farrigan, T. (2012). Characteristics and influential factors of food deserts. Technical report. 7

[32] Fang, L., Chen, P., and Liu, S. (2007). Particle swarm optimization with simulated annealing for tsp. In *Proceedings of the 6th WSEAS International Conference on Artificial Intelligence, Knowledge Engineering and Data Bases*, pages 206–210. 21

[33] Ferenchak, N. N. and Katirai, M. (2015). Commute mode and mental health in major metropolitan areas. *Transportation letters*, 7(2):92–103. 6, 7

[34] Fu, L. (2002a). Scheduling dial-a-ride paratransit under time-varying, stochastic congestion. *Transportation Research Part B: Methodological*, 36(6):485–506. 12

[35] Fu, L. (2002b). A simulation model for evaluating advanced dial-a-ride paratransit systems. *Transportation Research Part A: Policy and Practice*, 36(4):291–307. 3, 11

[36] Gandomi, A. H., Yang, X.-S., Talatahari, S., and Alavi, A. H. (2013). Metaheuristic algorithms in modeling and optimization. *Metaheuristic applications in structures and infrastructures*, 1:1–24. 18, 20

[37] Ghoulmie, F., Cont, R., and Nadal, J.-P. (2005). Heterogeneity and feedback in an agent-based market model. *Journal of Physics: condensed matter*, 17(14):S1259. 12

[38] Gralla, E. and Goentzel, J. (2018). Humanitarian transportation planning: Evaluation of practice-based heuristics and recommendations for improvement. *European Journal of Operational Research*, 269(2):436–450. 20

[39] Häll, C. H., Lundgren, J. T., and Värbrand, P. (2008). Evaluation of an integrated public transport system: a simulation approach. *Archives of Transport*, 20(1-2):29–46. 11

[40] Häll, C. H., Lundgren, J. T., and Voss, S. (2015). Evaluating the performance of a dial-a-ride service using simulation. *Public Transport*, 7(2):139–157. 2, 11

[41] Hämäläinen, W. (2006). Class np, np-complete, and np-hard problems. *Sort*, pages 1–7. 17

[42] Hess, D. B. and Lombardi, P. A. (2005). Governmental subsidies for public transit: History, current issues, and recent evidence. *Public works management & policy*, 10(2):138–156. 4

[43] Hetherington, J. H. and Willard, F. (1975). Two-, three-, and four-atom exchange effects in bcc. *Phys. Rev. Lett. 35, 144 (1975)*. iv

[44] Hochba, D. S. (1997). Approximation algorithms for np-hard problems. *ACM Sigact News*, 28(2):40–52. 17

[45] Hoffman, K. L., Padberg, M., Rinaldi, G., et al. (2013). Traveling salesman problem. *Encyclopedia of operations research and management science*, 1:1573–1578. 16

[46] Huang, B., Wu, Q., and Zhan, F. (2007). A shortest path algorithm with novel heuristics for dynamic transportation networks. *International Journal of Geographical Information Science*, 21(6):625–644. 18

[47] Ilavarasi, K. and Joseph, K. S. (2014). Variants of travelling salesman problem: A survey. In *International conference on information communication and embedded systems (ICICES2014)*, pages 1–7. IEEE. 17

[48] Jia, Y., Xu, W., and Liu, X. (2017). An optimization framework for online ride-sharing markets. In *2017 IEEE 37th international conference on distributed computing systems (ICDCS)*, pages 826–835. IEEE. 10

[49] Jiang, C., Wan, Z., and Peng, Z. (2020). A new efficient hybrid algorithm for large scale multiple traveling salesman problems. *Expert Systems with Applications*, 139:112867. 16

[50] Jing, Q.-L., Liu, H.-Z., Yu, W.-Q., and He, X. (2022). The impact of public transportation on carbon emissions—from the perspective of energy consumption. *Sustainability*, 14(10):6248. 4

[51] Jünger, M., Reinelt, G., and Rinaldi, G. (1995). The traveling salesman problem. *Handbooks in operations research and management science*, 7:225–330. 16

[52] KAT (2022). Knoxville area transit. 4, 61, 63

[53] Katayama, K. and Narihisa, H. (1999). Iterated local search approach using genetic transformation to the traveling salesman problem. In *Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation-Volume 1*, pages 321–328. 21

[54] Kii, M., Isikawa, R., and Kometani, Y. (2023). Toward a carbon neutral urban transportation system in japan. *IATSS Research*. 3

[55] Kizilateş, G. and Nuriyeva, F. (2013). On the nearest neighbor algorithms for the traveling salesman problem. In *Advances in Computational Science, Engineering and Information Technology: Proceedings of the Third International Conference on Computational Science, Engineering and Information Technology (CCSEIT-2013), KTO Karatay University, June 7-9, 2013, Konya, Turkey-Volume 1*, pages 111–118. Springer. 19

[56] Kline, A. G., Ahner, D. K., and Lunday, B. J. (2020). A heuristic and metaheuristic approach to the static weapon target assignment problem. *Journal of Global Optimization*, 78:791–812. 18

[57] Klügl, F. and Bazzan, A. L. (2012). Agent-based modeling and simulation. *Ai Magazine*, 33(3):29–29. 12

[58] Kumar, S. N. and Panneerselvam, R. (2012). A survey on the vehicle routing problem and its variants. 12

[59] Lau, H. C., Sim, M., and Teo, K. M. (2003). Vehicle routing problem with time windows and a limited number of vehicles. *European journal of operational research*, 148(3):559–569. 17

[60] Lemoine, P. D., Cordovez, J. M., Zambrano, J. M., Sarmiento, O. L., Meisel, J. D., Valdivia, J. A., and Zarama, R. (2016). Using agent based modeling to assess the effect of increased bus rapid transit system infrastructure on walking for transportation. *Preventive medicine*, 88:39–45. 13

[61] Li, S., Kahn, M. E., and Nickelsburg, J. (2015). Public transit bus procurement: The role of energy prices, regulation and federal subsidies. *Journal of Urban Economics*, 87:57–71. 4

[62] Litman, T. (2012). *Evaluating public transportation health benefits*. Victoria Transport Policy Institute Victoria, BC, Canada. 9

[63] Loukas, C. (2023). Kpd: Impaired driver killed 24-year-old who helped pave the way for children with special needs. 5, 6

[64] Lourenço, H. R., Martin, O. C., and Stützle, T. (2003). Iterated local search. In *Handbook of metaheuristics*, pages 320–353. Springer. 21

[65] Lucena, A. (1990). Time-dependent traveling salesman problem–the deliveryman case. *Networks*, 20(6):753–763. 16

[66] Ma, X. and Liu, Q. (2010). A particle swarm optimization for steiner tree problem. In *2010 Sixth International Conference on Natural Computation*, volume 5, pages 2561–2565. IEEE. 21

[67] Macal, C. M. and North, M. J. (2009). Agent-based modeling and simulation. In *Proceedings of the 2009 winter simulation conference (WSC)*, pages 86–98. IEEE. 3

[68] Michalewicz, Z. and Fogel, D. B. (2013). *How to solve it: modern heuristics*. Springer Science & Business Media. 18

[69] Nievergelt, J. and Preparata, F. P. (1982). Plane-sweep algorithms for intersecting geometric figures. *Communications of the ACM*, 25(10):739–747. 19

[70] Nurcahyo, G. W., Alias, R. A., Shamsuddin, S. M., and Sap, M. N. M. (2002). Sweep algorithm in vehicle routing problem for public transport. *Jurnal Antarabangsa Teknologi Maklumat*, 2:51–64. 19

[71] Ombuki, B., Ross, B. J., and Hanshar, F. (2006). Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence*, 24:17–30. 15

[72] Papadimitriou, C. H. and Steiglitz, K. (1998). *Combinatorial optimization: algorithms and complexity*. Courier Corporation. 17

[73] Pérez, F. A. A., Ortiz, G. E. R., Muñiz, E. R., Sacarello, F. J. O., Kang, J. E., and Rodriguez-Roman, D. (2020). Predicting trip cancellations and no-shows in paratransit operations. *Transportation Research Record*, 2674(8):774–784. 10, 11

[74] Potvin, J.-Y. (1996). Genetic algorithms for the traveling salesman problem. *Annals of Operations Research*, 63:337–370. 20, 21

[75] Ramachandran, P. (2009). Vehicle routing problem with load compatibility constraints. In *2009 IEEE International Conference on Industrial Engineering and Engineering Management*, pages 339–343. IEEE. 15

[76] Ramalhinho-Lourenço, H., Martin, O. C., and Stützle, T. (2000). Iterated local search. 22

[77] Rogers, T. N., Rogers, C. R., VanSant-Webb, E., Gu, L. Y., Yan, B., and Qeadan, F. (2020). Racial disparities in covid-19 mortality among essential workers in the united states. *World medical & health policy*, 12(3):311–327. 7

[78] Sáez, D., Cortés, C. E., Milla, F., Núñez, A., Tirachini, A., and Riquelme, M. (2012). Hybrid predictive control strategy for a public transport system with uncertain demand. *Transportmetrica*, 8(1):61–86. 12

[79] Santos, M. D. d., Silva, M. F., Velloza, L. A., and Pompeu, J. E. (2017). Lack of accessibility in public transport and inadequacy of sidewalks: effects on the social participation of elderly persons with functional limitations. *Revista Brasileira de Geriatria e Gerontologia*, 20:161–174. 5

[80] Schoemaker, P. J. (1991). The quest for optimality: A positive heuristic of science? *Behavioral and brain sciences*, 14(2):205–215. 18

[81] Sunio, V., Peckson, P., and Ugay, J. C. (2021). How urban social movements are leveraging social media to promote dignified mobility as a basic human right. *Case studies on transport policy*, 9(1):68–79. 8

[82] Tafreshian, A., Abdolmaleki, M., Masoud, N., and Wang, H. (2021). Proactive shuttle dispatching in large-scale dynamic dial-a-ride systems. *Transportation Research Part B: Methodological*, 150:227–259. 10, 11, 14

[83] Tao, F., Xiao, B., Qi, Q., Cheng, J., and Ji, P. (2022). Digital twin modeling. *Journal of Manufacturing Systems*, 64:372–389. 13

[84] Taunk, K., De, S., Verma, S., and Swetapadma, A. (2019). A brief review of nearest neighbor algorithm for learning and classification. In *2019 international conference on intelligent computing and control systems (ICCS)*, pages 1255–1260. IEEE. 19

[85] Uğur, A. and Aydin, D. (2009). An interactive simulation and analysis software for solving tsp using ant colony optimization algorithms. *Advances in Engineering software*, 40(5):341–349. 3

[86] Urciuoli, L. (2018). The risk of standards proliferation–an analysis of differences between private and public transport standards. *Transportation research part A: policy and practice*, 116:591–602. 25

[87] VanDerHorn, E. and Mahadevan, S. (2021). Digital twin: Generalization, characterization and implementation. *Decision support systems*, 145:113524. 13

[88] Vuchic, V. R. (2002). Urban public transportation systems. *University of Pennsylvania, Philadelphia, PA, USA*, 5:2532–2558. 10

[89] Wang, K.-P., Huang, L., Zhou, C.-G., and Pang, W. (2003). Particle swarm optimization for traveling salesman problem. In *Proceedings of the 2003 international conference on machine learning and cybernetics (IEEE cat. no. 03ex693)*, volume 3, pages 1583–1585. IEEE. 21

[90] Xiang, Z., Chu, C., and Chen, H. (2006). A fast heuristic for solving a large-scale static dial-a-ride problem under complex constraints. *European journal of operational research*, 174(2):1117–1139. 14

[91] Xiang, Z., Chu, C., and Chen, H. (2008). The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments. *European Journal of Operational Research*, 185(2):534–551. 15

[92] Yang, J., Shi, X., Marchese, M., and Liang, Y. (2008). An ant colony optimization method for generalized tsp problem. *Progress in Natural Science*, 18(11):1417–1422. 21

[93] Yoh, A., Iseki, H., Smart, M., and Taylor, B. D. (2011). Hate to wait: Effects of wait time on public transit travelers' perceptions. *Transportation Research Record*, 2216(1):116–124. 1

[94] Zhan, S.-h., Lin, J., Zhang, Z.-j., Zhong, Y.-w., et al. (2016). List-based simulated annealing algorithm for traveling salesman problem. *Computational intelligence and neuroscience*, 2016. 20, 21

[95] Zhen, C. (2021). Food deserts: myth or reality? *Annual Review of Resource Economics*, 13:109–129. 7

Appendices

Vita

Kimon Ewalt Swanson was born in Knoxville, TN on June 10, 1998. He was the firstborn of 3 children. He would graduate high school with honors and attend The University of Tennessee in Knoxville. There he would receive his Undergrad and Graduate degrees in Industrial Systems Engineering. Following college, he plans to branch away from the academic world and enter the business world.