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Master's Thesis

Integrating Dynamic Ride-Sharing in MATSim

Assessing the Impacts of Dynamic Ride Sharing on the Environment.
The Case Study of Upper Austria

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Abstract

Dynamic ride-sharing (DRS), enabled by technology, has the potential to revolutionize the way people travel, offering an efficient and cost-effective alternative to individual travel. By facilitating the process of matching drivers and riders, DRS can significantly reduce the number of single-occupancy vehicles on the road, thereby mitigating traffic congestion and reducing carbon emissions. However, promoting DRS is a complex challenge that requires careful planning and strategic interventions. Before implementing any measures, it is crucial to evaluate their effectiveness, as some policies and measures may have unintended consequences on the transport system and the environment. This research focuses on the integration of DRS as a novel mode in the agent-based framework, MATSim. The aim is to provide a tool that can evaluate the effects of different DRS interventions on the whole transport system. The thesis proposes a methodology for integrating DRS into MATSim and develops and tests the extension. A case study is conducted using this new extension to assess the impacts of financial incentives for drivers on reducing vehicle km travelled. The results show that this measure could lead to an increase in vehicle kilometers travelled due to driving being more attractive. The findings of this study highlight the benefits of utilizing agent-based models such as MATSim for modeling DRS and gaining a comprehensive understanding of its impacts on the transportation system. Despite the advantages of integrating DRS in MATSim, the study also identified some limitations which can be addressed through further research and extension of the model.

Keywords: MATSim, agent-based modeling, dynamic ride-sharing, carpooling, financial incentives.

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List of Abbreviations

ABM agent based modelling

DRS dynamic ride-sharing

GHG green house gas

HH house hold

MATSim Multi-Agent Transport Simulation

OD origin-destination

OSM open street map

PT public transport

VKT vehicle kilometers travelled

1 Introduction

This chapter provides a comprehensive introduction to the thesis, demonstrates research motivation, states the expected contributions, and defines the structure of this thesis.

1.1 Introduction

Rapid urbanization and population growth in cities have led to an increase in the number of vehicles on the road, resulting in traffic congestion, longer travel times, and negative environmental impacts such as air pollution and green house gas (GHG) emissions. Additionally, relying on private cars as the primary mode of transportation deepens social inequalities and impedes vulnerable populations' accessibility. As such, policymakers and urban planners are increasingly focused on finding innovative solutions to reduce car dependency, encourage sustainable transportation and increase system efficiency.

Advanced technological solutions have paved the way for new mobility solutions. One of these solutions is dynamic ride-sharing (DRS). Unlike traditional carpooling which limits drivers and riders to their acquaintances, DRS relies on real-time information and communication technologies to match drivers with riders in an efficient manner. This advanced innovation allows drivers and riders to find more compatible matches and, subsequently, increase the number of shared rides. Thus, reducing traffic congestion, air pollution, and overall travel costs. Given the numerous benefits of DRS, many cities are interested in implementing policies to promote DRS further.

1.2 Motivation

Evaluating the potential impacts of transport policies is critical to making informed decisions that achieve the desired outcomes. Transport modeling and simulations are effective methods for evaluating potential impacts as it helps to visualize and test the effectiveness of a proposed transport measure or policy in a virtual environment. Modeling and simulation can also help policy makers predict and mitigate unintended consequences ensuring that the measures align with the overall strategies.

However, transport modeling is a diverse field that encompasses a wide range of methods and techniques. One such method is agent based modelling (ABM), which simulates the behavior of individual agents and their interactions with the transportation system.

ABM offers several advantages over traditional modeling approaches, as it captures the complexity of human behavior and the spatio-temporal dynamics of transportation systems. It can also provide insights into the impacts of policies and interventions on individual and collective behavior.

Furthermore, ABM can be a powerful tool for modeling DRS compared to other modeling tools. Unlike traditional transport models, ABM focuses on the behavior and decision-making of individual agents, such as DRS users, rather than macro-level variables like traffic flow. This allows ABM to capture the complexity and heterogeneity of individual travel behaviors and preferences, as well as the social interactions and network effects that can influence DRS adoption. Additionally, ABM can model the spatio-temporal dynamics of DRS, including the pickup and dropoff locations of DRS users and the impact on traffic flow and congestion.

1.3 Expected Contribution

This thesis aims to integrate DRS as a novel mode of transportation within the open source framework, Multi-Agent Transport Simulation (MATSim). By examining previous implementations of DRS models, the thesis investigates the current state of research in this area, as well as identifies their limitations. The study aims to learn from previous approaches and build upon them to develop an effective approach to integrating the DRS extension in MATSim.

The new extension is used to analyse the potential impacts of providing money incentives for DRS drivers on the transportation system and environment in Upper Austria. The results provide insights into the potential benefits and trade-offs associated with the implementation of such incentives in the region, and highlight the need for a holistic and integrated approach to transportation planning and policy-making.

By developing and utilizing this new DRS extension within MATSim, this thesis aims to provide a valuable tool for policymakers and urban planners to accurately assess the impact of DRS policies and interventions on transport systems and the environment.

1.4 Framework

This thesis is composed of six chapters. The first chapter serves as an introduction, providing an overview of the thesis and defining its motivation and contributions. In the second chapter, a literature review is conducted with two primary objectives: to gain insights from previous research and to identify research gaps that will be addressed in this study.

The third chapter outlines the methodology used in this research, providing detailed explanations of the extension development and methods employed. In the fourth chapter, the results are presented while chapter five elaborates on the obtained results. Finally, the sixth chapter serves as the conclusion, where the lessons learned are presented along with possible applications, limitations and future research.

2 Literature Review

This chapter is divided into five sections. The first section clarifies the difference between ride-sharing, carpooling and dynamic ride-sharing. The second section reviews the various factors that can influence DRS users decisions. The third section identifies potential policies and interventions that can be implemented to encourage greater adoption of DRS. Section four provides an overview of the current literature on modeling and evaluating the impact of ride-sharing, while the fifth and final section defines the research gaps and outlines the relevant research questions.

2.1 Ride-Sharing

In existing literature, authors are using terms such as carpooling, ride-sharing, and dynamic ride-sharing interchangeably [1]. This section aims to clarify these terms and highlights the different types.

2.1.1 Definitions

Ride-sharing is a general term when multiple individuals share a single vehicle to reach a common destination [2], [3]. One classic form of ride-sharing is acquaintance-based carpooling, where a group of individuals who know each other, such as co-workers, friends, or neighbours, share a ride in a single vehicle. In this arrangement, participants usually take turns driving and contribute to the cost of fuel and other expenses [4].

However, with the rise of technology, a new form of ride-sharing has emerged called dynamic ride-sharing. Unlike traditional carpooling, which limits drivers and riders to only their acquaintances, DRS uses platforms and mobile apps to connect drivers with riders on a trip by trip basis. This allows for greater flexibility of matching drivers with riders on short notice ranging from a few minutes to a few hours[5]–[8].

2.1.2 Categories

Ride-sharing can be categorized in various ways. One of the most common categorizations is based on the relation between the users. Ride-sharing can involve acquaintances, strangers or ad hoc. Ride-sharing between acquaintances can be between family members, neighbours or coworkers. Whereas, ad hoc is when a ride is shared with someone who happens to be going in the same direction, also called slugging [9].

On the other hand, ride-sharing between strangers also called organised-based ride-sharing can be categorized based on the technology used to find a rider. For example, some rides are organised through websites or phone calls while other rides are organised using mobile apps [9]. The latter is the only one considered as DRS since it is based on matching algorithms that finds and suggests matches for the user. The various classifications of ride-sharing are demonstrated in Figure 2.1.

In addition, DRS may differ depending on the trip distance, ranging from intra-city trips to inter-city travel [9]. DRS can also be arranged on the fly or up to several days in advance. However, It is preferable for individuals to arrange a shared ride at least one night in advance, rather than at the last minute just before the trip [7]. An additional form of DRS that is still less popular is drivers accepting ride requests while en route. This method poses several safety concerns, which have presented significant challenges for its implementation [6].

In light of the findings from the literature review, this thesis will solely focus on a specific type of DRS, where drivers and riders use matching apps and platforms to find a match in advance, rather than directly or en route. The drivers in this context are also not doing this for a living, but rather just sharing a ride.

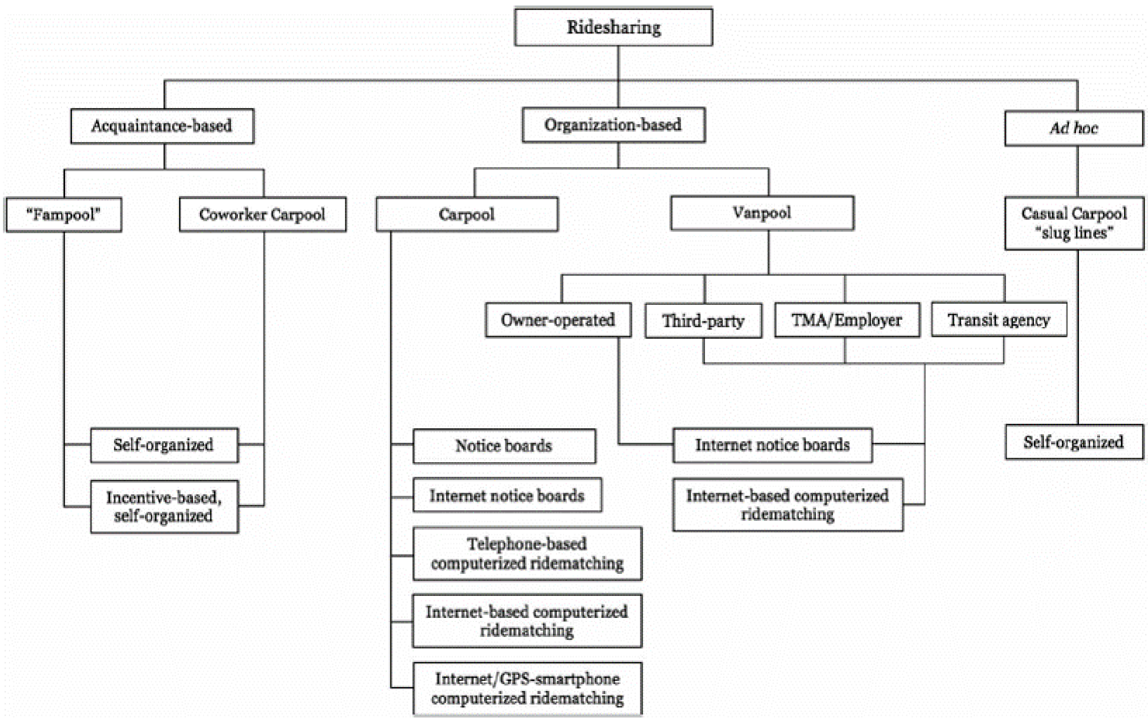

Figure 2.1: Ride-sharing categories [9]

2.2 User Perspective

In order to efficiently promote DRS, it is important to understand the motivations, psychology, and obstacles that users face. Thus, a comprehensive review of existing literature about DRS user perspective and travel behavior is necessary [1]. Factors affecting drivers and riders decisions can be classified into four categories; sociodemographics, mode related factors, situational factors and judgmental factors [10], [11]. Table 2.1 shows the different factors affecting the users decisions.

Table 2.1: Dynamic ride-sharing factors, table compiled from [10]–[14]

Sociodemographics	Mode related	Situational	Judgemental
Gender	Organisation time	Trip distance	Awareness
Age	Waiting time	Time of trip	Ease of use
Income	Travel time	Travel schedule	Safety
HH size	Parking time	Alternative modes	Comfort
Car availability	Parking cost	Population density	Flexibility
Native	Travel cost	DRS platforms	Privacy
	Reliability		

2.2.1 Sociodemographics

Sociodemographic factors are characteristics of individuals that can affect their decision-making process when using DRS services. Gender, age, income, house hold (HH) size, car availability, and native status are all examples of sociodemographic factors that can impact a user's decision [1].

For instance, women may be more concerned about safety when using DRS services, while younger users may be more focused on cost-effectiveness [14]. Income can also affect users' willingness to use DRS services [1], while native status can influence users' familiarity and comfort when using these services[15].

Understanding the different sociodemographic factors and how they impact users can help DRS service providers create targeted incentives and improve their services to meet the needs of different user groups.

2.2.2 Mode Related Factors

Mode-related factors are crucial factors that DRS users take into account. Cost-effectiveness is often a key consideration, with users seeking to save on travel and parking costs [9]. However, users may also face certain drawbacks such as longer waiting and travel times, as well as the need to spend additional time organizing their ride before the trip [11]. Additionally, DRS services may not always be reliable, which can be a concern for users who prioritize consistency and reliability [10].

2.2.3 Situational Factors

Situational factors refer to the circumstances surrounding the user's trip, such as trip distance, trip departure time, schedule flexibility, alternative modes condition, population density, and DRS platform availability and quality [1].

The duration of the trip and the departure time are two factors that can significantly impact the user decision [10]. Additionally, areas with reliable and efficient public transport (PT) systems may reduce the likelihood of using DRS services, as users may prefer the convenience and reliability of PT [2], [16].

Population density is another situational factor, as a high population density increases the chance of finding a compatible ride match [2], [10]. Furthermore, having a fixed travel schedule can contribute to consistent user behavior [1]. Moreover, the availability and quality of DRS platforms are crucial considerations that can sway a user's decision, as users tend to favor platforms that are reliable and have a bigger user base [17].

2.2.4 Psychological Factors

Psychological factors such as perceived ease of use, safety, privacy, comfort, flexibility and environmental awareness can also play a role on the user's choice. For example, a user may prefer a DRS service that is easy to use, with an intuitive interface [2]. Environmental awareness may also influence the user to reduce emissions footprint by sharing rides with others [1], [10]. Factors like safety and privacy are also critical considerations for users [18].

2.3 Policies and Interventions

Encouraging commuters to DRS remains a challenge. Solo-commutes continue to account for the majority of car travel [19].

Technology has enabled the development of DRS platforms that can effectively connect and match more people than traditional ride-sharing methods. However, the success of these platforms depends on their ease of use and their ability to cater to local needs [2], [5], [9].

Additionally, it's important to ensure that the platforms can attract a wider user base. Many platforms are not initially designed to be scalable, which would make it challenging to reach a critical mass, reducing the chances of users finding a suitable ride match [17].

Therefore, developing DRS city-wide platform or establishing interoperability among numerous DRS databases could significantly improve the user experience [2], [9]. Open source data sharing among DRS platforms could enable members to find matches across all databases.

Moreover, destination-based DRS programs have a higher likelihood of success. For instance, workplaces is a typical destination for employees within a company who often share similar departure times and sociodemographic characteristics. Thus, it's essential to form partnerships with regional and large employers to encourage their workers to participate in DRS services [20].

It should be emphasized that developing a DRS platform alone is not sufficient to guarantee a critical mass. DRS platforms should be accompanied by various interventions to encourage users to share rides [21].

These interventions may include reduced parking costs, whether at park and ride (PR) facilities or at the destination parking facility [7], [9], [22], as well as prioritized parking for DRS users [21]. Additionally, financial incentives could be provided to drivers to encourage them to share their vehicle [7], [9], [23]. The provision of HOV lanes can also improve the efficiency of DRS services [9].

To further enhance the effectiveness of DRS services, mobility guarantees could be implemented [2], [21], such as providing a taxi or a shuttle in case a rider couldn't find a match. Environmental awareness campaigns [9], [21] and marketing initiatives can also be effective in promoting the benefits of DRS services [7], [9], as many people may not be aware of the DRS possibilities available to them.

Overall, it is essential to consider a range of interventions that complement the technology-facilitated DRS matching platforms to encourage users to adopt DRS services effectively. Table 2.2 shows the different interventions and policies collected from literature that can promote DRS.

2.4 Modeling Dynamic Ride-Sharing

This section provides an overview of existing literature that has examined and constructed models for ride-sharing.

Table 2.2: Dynamic ride-sharing interventions (own illustration)

Policies and Interventions
Financial incentives
User friendly platforms
Marketing strategies
HOV lanes
Mobility guarantee
Reduced parking costs
Environmental Awareness campaigns
Prioritized parking
Destination based programs
Integrated platform

2.4.1 Statistical Models

For a meta analysis, two papers assembled studies from 1981 till 2013 and from 2014 till 2018 related to evaluating and modeling ride-sharing [1], [10]. The assembled studies attempted to understand the factors influencing the behavior of ride-sharing users and non-users, as well as to evaluate the impact of different interventions and policies using statistical models.

In examining the factors influencing commuters' mode choice and ride-sharing behavior, various researchers employed different methods. For instance, [24] used a nested logit model to evaluate the impact of interventions such as parking priority, HOV lanes, and financial incentives on mode choice, while [25] used an ordered probit model. [26], on the other hand, employed a multinomial logit model to assess the effect of parking cost on mode choice.

[27] used a hybrid discrete choice model to calculate the interventions' impact on commuters, and [28] used a multilevel regression model to evaluate the impact of work location on large workplace commuters' decisions. Different regression models such as logistic, ordered logit, stepwise and probit were also used to study the determinants of ride-sharing behavior [29]–[32]. Table 2.3 shows the assembled studies objectives and methodologies used.

Table 2.3: Studies and methodologies, table compiled from [1], [10]

Study	Objective	Methodology
[26]	Parking cost impact on commuter mode choice	Multinomial logit model

Continued on next page...

Table 2.3 – Continued from previous page

Study	Objective	Methodology
[25]	HOV/parking priority/mobility guarantee/incentives impact on mode choice	Ordered probit model
[29]	Sociodemographics correlation with commuter mode choice	Logistic regression analysis
[27]	Interventions impact on commuters mode choice	Hybrid discrete choice model
[24]	HOV/parking priority/incentives impact on commuters mode choice	Nested logit model
[28]	Location and promotions impact on large workplaces commuters	Multilevel regression model
[33]	Determinants of ride-sharing behaviour	Logistic regression analysis
[34]	Immigrants' propensity to ride share	Multinomial logistic regression
[35]	Effect of ride-sharing interventions	Multinomial logit model
[36]	Ride-sharing potential in non-metropolitan areas	Binomial logistic regression
[37]	Factors simulating commuters to ride share	Mixed multinomial logit model
[38]	Potential for peer-to-peer ride-sharing system	Ordered logit regression
[39]	Impact of ride-sharing interventions	Multiple regression
[40]	Preferences to create ride-sharing system	Stated preferences regression
[30]	Ride-sharing users behaviour in France	Ordered logit regression
[31]	Motivations underlying ride-sharing	Stepwise regression
[32]	Factors affecting individuals' ride-sharing decisions	Probit regression

2.4.2 Agent-Based Models

ABM offers several benefits for modeling DRS, including its ability to capture the complex interactions between agents and simulate their behaviors under different scenarios. However, there is currently limited literature on the use of ABM for modeling DRS.

For instance, [41] used ABM to simulate the interactions of agents and to analyze the effects of change in factors related to the infrastructure, behavior and cost. They use agent profiles and social networks to initiate the agent communication model and then employ a route matching algorithm and a utility function to model the negotiation process between agent.

Whereas, [42] presented a conceptual design of ABM of a set of ride-sharing users. The proposed model is used for simulating the interactions between agents. The model enables communication to trigger the negotiation process. Furthermore, it measures the effect of pickup-dropoff on the ride-sharing trips.

Unlike previous studies, [43] used the ABM simulation framwork MATSim, which enables large-scale transport simulations involving various transport modes [44]. In their study, DRS was integrated in MATSim, enabling drivers to accept ride requests while en route.

2.5 Research Gap and Questions

This section defines the research gaps and outlines the research hypothesis and relevant research questions that will be addressed in this thesis.

2.5.1 Research Gaps

Several research gaps that exist in the existing literature on modeling DRS are addressed in this section. Firstly, the statistical models used in previous studies were limited in their ability to represent real behaviour as they relied on stated preference data. Furthermore, these models didn't consider other factors that could influence ride-sharing adoption, which were identified in section 2.2.

Secondly, the agent-based models that have been developed thus far have only focused on modeling the matching and communication between agents, assuming that the agents are already willing to use DRS. Thirdly, there has been a lack of research conducted on modeling DRS within a whole multi-modal transport system.

Finally, while one paper has utilized MATSim to model DRS within a whole transport system, this model was limited by its implementation of DRS while agents are already en route, which is an application that is still not widely implemented due to safety concerns and advanced technology requirements.

2.5.2 Research Questions

The purpose of this research is to incorporate DRS into MATSim to simulate the behavior of DRS agents and include DRS as one of their transportation options. The study will use the newly developed extension to evaluate the potential impact of financial incentives for DRS drivers on reducing vehicle kilometers travelled (VKT).

The hypothesis is that providing DRS drivers with financial incentives would increase the number of shared rides anc consequently reduce VKT.

To determine the validity of the hypothesis, the thesis will address the following research questions:

1) How could the DRS behavior of drivers and riders be modelled in MATSim?

2) What is the impact of financial incentives for DRS drivers on reducing the VKT?

3 Methodology

This chapter is divided into four sections. The first section examines the MATSim cycle and its components, while the second section outlines the necessary steps to simulate DRS. The third section involves integrating these steps into the MATSim cycle. Whereas the final section, section four, describes the scenarios preparation process. The methodology workflow is illustrated in Figure 3.1.

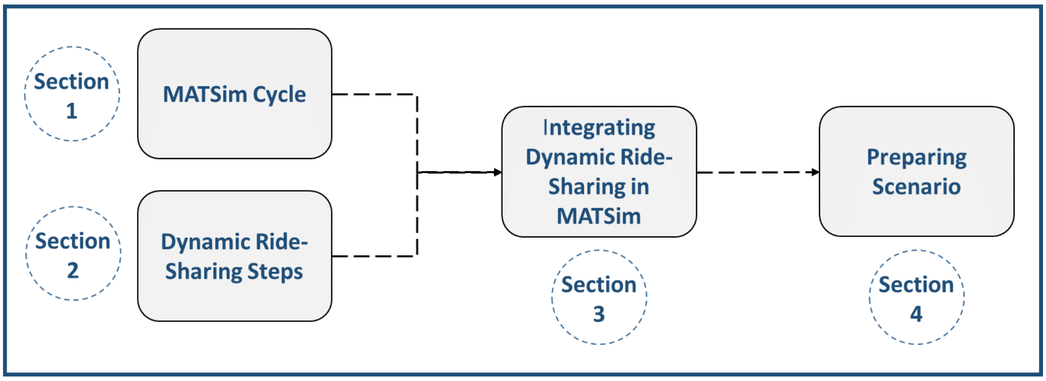

Figure 3.1: Methodology workflow (own illustration)

3.1 MATSim Cycle

MATSim is a co-evolutionary transport simulation framework, that was developed by Kay Axhausen from ETH Zurich and Kai Nagel from TU Berlin. In MATSim, each agent optimizes its daily activity schedule over iterations [44]. A MATSim simulation involves a configurable number of iterations, which are represented by the cycle shown in Figure 3.2.

3.1.1 Initial Demand

In MATSim, individuals are represented as "agents." Each agent is initially assigned at least one plan that includes activities and legs. Typically, agents' plans are generated based on empirical data using either sampling or discrete choice modeling techniques [44].

3.1.2 Execution

In MATSim, the execution step involves taking one "selected" plan per agent and implementing it in a synthetic reality, also called network loading. To simulate traffic flow, MATSim employs a spatial queue representation [44].

3.1.3 Scoring

Scoring in MATSim can be perceived as utilities. After each iteration, all agents evaluate the score of their executed plans. Time spent in traveling is perceived negatively while time spent in activity is perceived positively [44].

3.1.4 Replanning

At the start of each iteration, some agents modify their plans based on various choice dimensions, such as route, mode, time of day, and location. Since other agents may also change their behavior, the previous score of a plan can be altered in subsequent iterations [44].

3.1.5 Analyses

After finishing simulation, MATSim generates various output files that provide information on the simulation results such as events file which includes all different types of events happened to agents during the simulation [44].

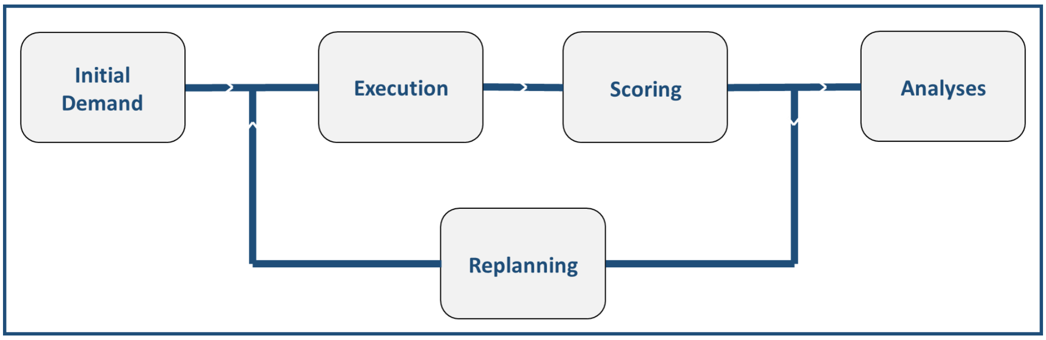

Figure 3.2: MATSim cycle[44]

3.2 Dynamic Ride-Sharing Steps

According to [41], the DRS process involves several steps, which include (i) generating a motivation to ride-share, (ii) communicating this motivation to other interested agents, (iii) negotiating a plan with the interested agents, (iv) implementing the agreed-upon plans, and (v) providing feedback to all concerned agents.

This thesis will draw inspiration from these steps to design a DRS procedure using an agent based approach. Step (i) would represent the generation of initial demand. Whereas, step (ii) stands for the matching algorithm. Step (iii) symbolizes the adjustments in plans needed to be done by the drivers and riders to perform ride-sharing, while step (iv) stands for the execution step and step (v) represents the score of the executed plan.

Since step (i) and (v) are already incorporated into MATSim, this section proposes a procedure consisting of steps (ii) (iii) and (iv) along with an additional step to model DRS agents within an ABM framework.

3.2.1 Matching Algorithm

The matching algorithm aims to find the best possible matching between drivers and riders, while considering the constraints of the system, such as vehicle capacity, pickup/dropoff locations, and arrival/departure times [45].

There are various ride-sharing system options available for both drivers and riders. A driver can offer a ride to either one or multiple riders. Similarly, a rider can request a ride with a single driver or multiple drivers, and transfer from one driver to another while en route to their destination [46]. Consequently, there are four fundamental ride-sharing system variants, as demonstrated in Table 3.1.

Table 3.1: Dynamic ride-sharing variants [46]

	Single Rider	Multiple Riders
Single Driver	Matching of pairs of drivers and riders	Routing of drivers to pickup and deliver riders
Multiple Drivers	Routing of riders to transfer between drivers	Routing of riders and drivers

To solve the DRS matching problem of 'multiple riders and single driver', 'multiple riders and multiple drivers' and 'single rider and multiple drivers', enumeration or brute-force search can be used, which involves trying every possible arrangement of ride-sharing routes. Even though it is a solution method that guarantees the optimal solution for small problems. For larger simulations, the magnitude of the set of possibilities is too high to be computationally feasible [47].

Other methods such as tabu search, ant colony optimization, genetic algorithm and simulated annealing, can be used to solve the DRS matching problem of multiple riders and drivers [47]. However, this thesis focuses only on matching pairs of single driver and single rider. The following steps and Figure 3.3 explain how the matching algorithm works.

- Requests Collection:

  In this step, drivers and riders send requests for every DRS trip they plan to take. These requests contain specific information, including the origin coordinates, destination coordinates, and departure time of the trip. For modeling and simplification purposes, it is assumed that all DRS drivers and riders requests are known in advance prior to the execution of the matching process.

- Zonal and Temporal Filtration:

  This step entails several key actions. Firstly, a grid of cells is created from the network. The size of the grid cell is a configurable value that can be adjusted. Next, each rider's origin and destination are allocated to their respective designated cells within the grid. Following this, the algorithm iterates over each driver and uses their request information to identify matching requests from riders. Specifically, the algorithm filters out requests that do not share the same origin and destination cells as the driver's request. Additionally, time segments are also created in this process. The time segments length is a configurable value that can be adjusted. The departure times of the riders are used to determine the appropriate time bin for each request. Only the requests with a departure time in a bin similar to the driver's departure time are considered. In this manner, the pool of candidate riders for each driver is narrowed down to only those whose requests meet the necessary criteria for a successful ride match.

- Departure Time Filtration:

  In this step, the riders who satisfy the aforementioned criteria are selected, and subsequently, the driver's estimated arrival time at the pickup point is computed. Then, the algorithm checks whether the driver's estimated arrival time at the pickup point falls within an acceptable range of the rider's willingness to adjust their departure time. Only riders matching this criteria would be selected to proceed to the next step. The riders' willingness to adjust their departure time is a configurable value that can be adjusted.

- Optimal Request Matching: In this step, the travel time of the driver's initial trip from the origin to the destination is calculated, and subsequently, the travel time of the trip if the driver performs a detour to pickup and dropoff the rider is calculated. For each rider, the algorithm computes the driver detour factor by dividing the 'driver travel time with detour' by the 'driver original travel time'. Subsequently, the rider with the lowest detour factor is selected as the match for the driver. Once matched, the rider and the driver are removed from the DRS pool, and the algorithm proceeds to the next driver.

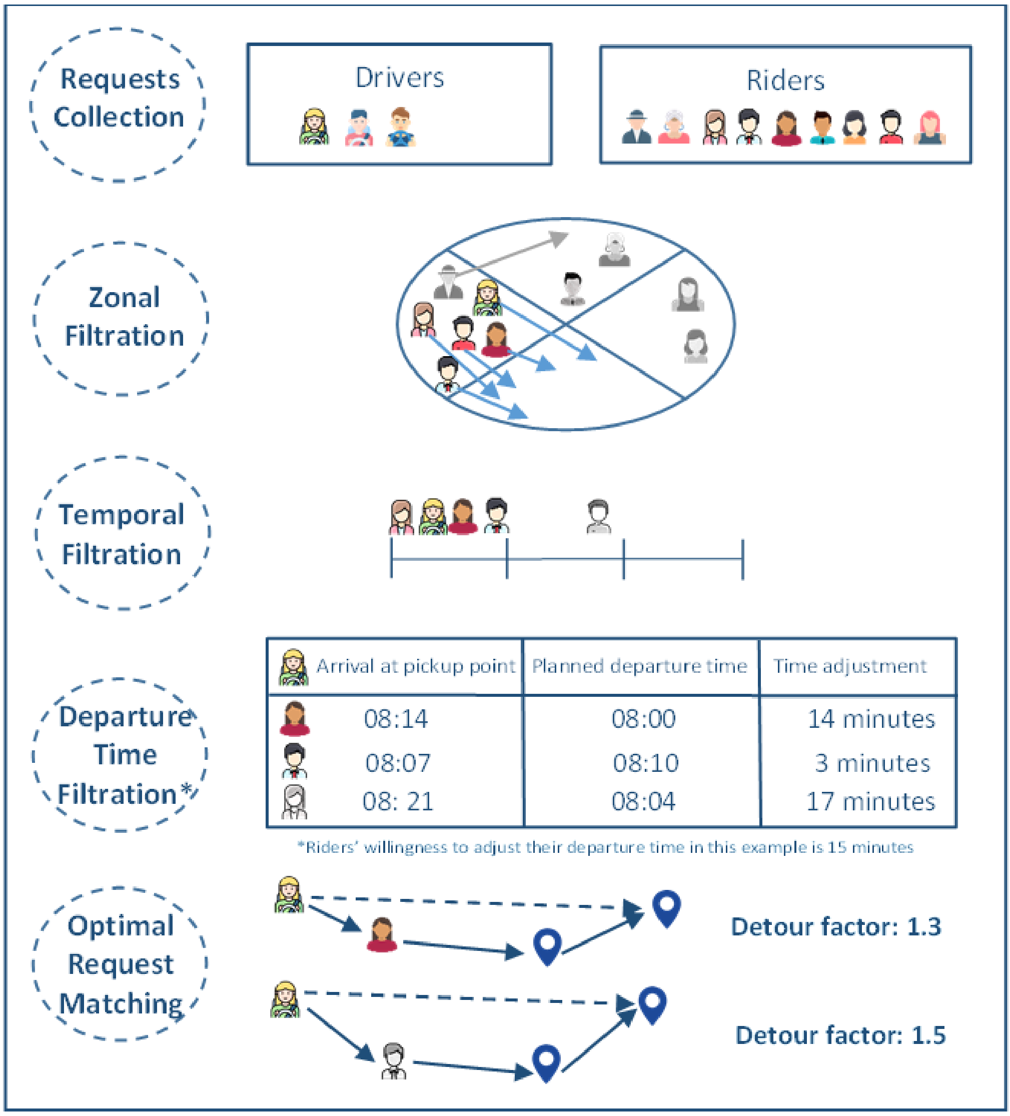

Figure 3.3: Matching algorithm (own illustration)

3.2.2 Plans Adjustment

Following the matching step, if a driver is successful in finding a match, their plan will be updated to include two new activities for pickup and dropoff with all relevant details including pickup location, dropoff location and pickup time. However, if a driver is unable to find a match, their original plan remains unchanged.

On the other hand, if a rider finds a match, they may need to adjust their departure time if the driver arrives earlier than the rider's planned departure time. If a rider is unable to find a match, no change will happen to their plan. Figure 3.4 shows the plans adjustment flow chart.

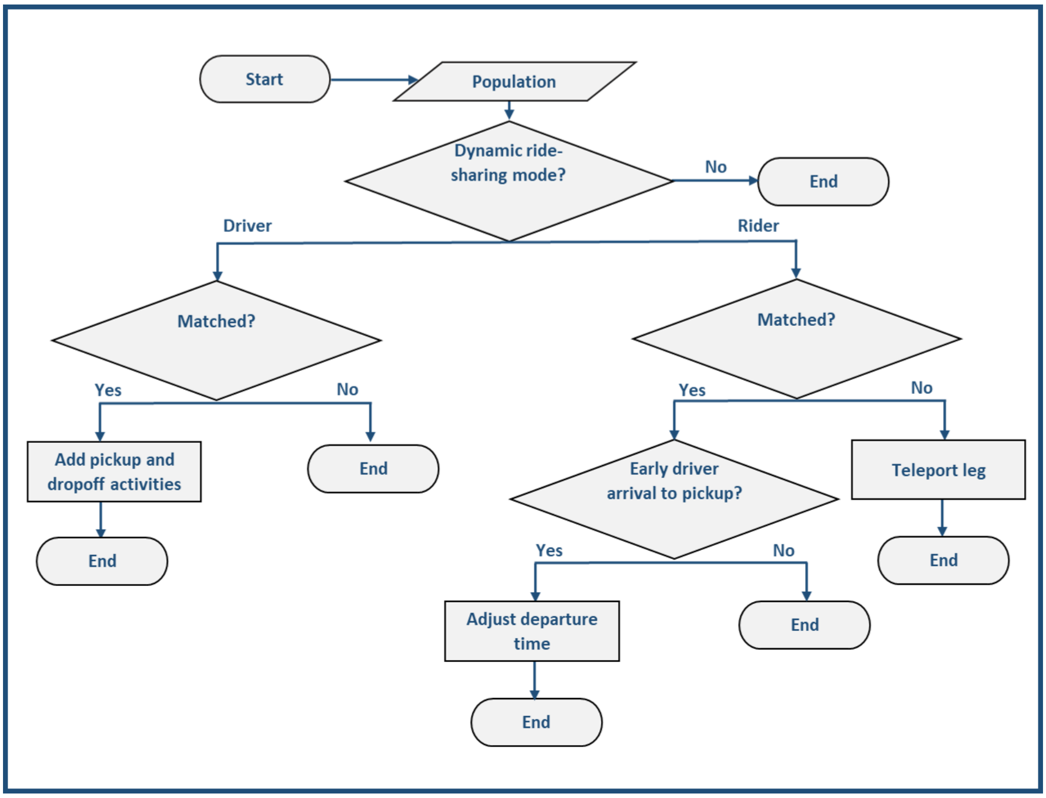

Figure 3.4: Plans adjustment flow chart (own illustration)

3.2.3 Plans Execution

After adjusting the plans, a set of rules are followed for plans execution. If a driver has a match, they will pick up the appropriate rider from the pickup point, drop them off at their destination, and then continue to their next activity. However, if a driver doesn't have a match, they will proceed directly to their next activity.

On the other hand, if a rider has a match, they will be picked up by the appropriate driver and dropped off at the drop-off point as per the planned route. However, if a rider doesn't have a match, they will be teleported to their destination with a low score to reflect the inconvenience of not being able to share a ride.

3.2.4 Undoing Plans Adjustments

After executing the plans, any changes made to the original plans are undone. For riders, this involves restoring the original departure time of their activities. Similarly, for drivers, any extra plan elements added to accommodate DRS are removed, thereby restoring the original plan. These steps ensure that the agents are ready for the next iteration, and any future DRS allocations in the next iterations can be made from a clean state.

3.3 Integrating Dynamic Ride-Sharing in MATSim

This section builds upon the previous two sections and provides an integration framework for the DRS steps within MATSim. Figure 3.5 shows DRS integration in MATSim.

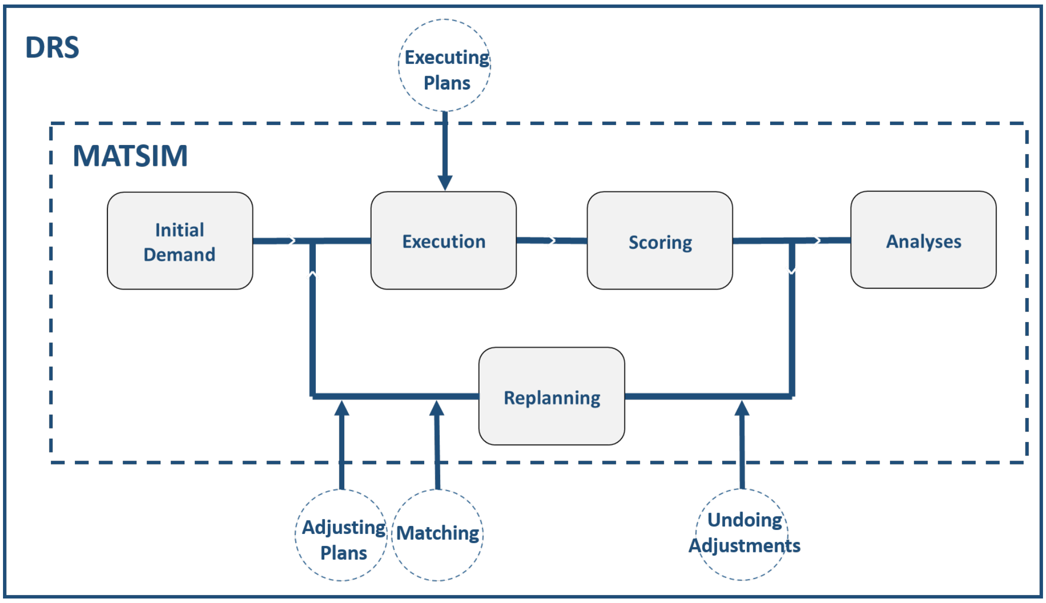

Figure 3.5: Dynamic ride-sharing integration in MATSim (own illustration)

3.3.1 Matching Algorithm in MATSim

MATSim provides the flexibility to extend its functionality through the use of controller listeners. This feature allows users to halt the simulation at specific points in the cycle and make necessary extensions or adjustments [48].

The 'ReplanningListener' in MATSim is used as the integration point for the matching algorithm. This algorithm is applied after agents have replanned and selected their travel modes. For each DRS trip, a driver or a rider request is created. In the beginning of each iteration, the requests are collected and shuffled to insure that each iteration the order of agents is not the same. The matching algorithm is then applied to pair drivers with riders. The resultant paired requests are stored and passed on to the subsequent step of plans adjustment.

3.3.2 Plans Adjustment in MATSim

In the same listener, the matched data between drivers and riders is utilized to modify the plans of these agents. For drivers, two new activities - pickup and dropoff - are added to their plans for each DRS trip, along with information about the pickup/dropoff locations and times. During the creation of the pickup activities, an additional attribute, "riderId", is included, tohelp link the driver and the rider later in the next steps.

The departure time of the rider may also be adjusted if the driver's arrival time at the pickup point is earlier than the planned departure time of the rider. If the activity departure time is modified, an attribute is added to the activity known as the "original departure time", which is also used in later steps of the process.

3.3.3 Plans Execution in MATSim

In MATSim, the execution of DRS agent trips is managed by an engine that implements three existing MATSim classes: 'MobsimEngine', 'ActivityHandle', and 'DepartureHandler'. These classes are responsible for handling agent activities and departures. The new engine implementation ensures that each matched rider waits for their designated driver to arrive. On the other hand, unmatched riders departure is handled by another MATSim engine which teleports them to their next destination.

The engine also takes on the task of managing pickup and dropoff activities of drivers. Using the riderId attribute of the pickup activity, the engine checks if any rider with such an Id is already waiting. If the rider is not waiting, the driver will wait until the end time of the pickup activity and leave if the rider does not show up. If the rider is waiting, they will enter the driver's vehicle, and both will stay in the vehicle until reaching the next activity, which is the dropoff activity. At the dropoff activity, the rider is removed from the vehicle.

Furthermore, the driver's profit is calculated by a function that determines the distance they drove together, multiplied by the profit per kilometer. The profit per kilometer is a configurable values that is set before the simulation. In MATSim, the drivers perform this money exchange using 'PersonMoneyEvent' which is a type of event in MATSim that can be thrown anywhere during the simulation and affects the overall monetary budgets of the agents.

3.3.4 Undoing Plans Adjustments in MATSim

This step implements the 'IterationStartsListener' to iterate through all agent plans before a new iteration starts and determine if any changes have been made to those with DRS mode. For drivers, it removes any DRS pickup and dropoff activities from their plans. Whereas, for riders, it checks whether any activities contain the attribute "original departure time" and sets the departure time of that activity to its original departure time.

3.4 Preparing Scenario

This section provides a comprehensive overview of the process of creating scenarios for the Upper Austria region using MATSim, with a focus on the newly integrated DRS extension.

3.4.1 Population

The synthetic population is based on the Austrian mobility survey "Österreich Unterwegs" from 2013/14 [49], which maps the mobility behavior of approximately 323,550 agents from 167,686 households, representing 25% of the mobile population over 6 years and corresponding to a total population of 1.295 million people (including cordon agents).

The agents use the modes of walking, cycling, PT, car and rider. The mode choice model is based on a travel survey conducted by the Vienna University of Economics and Business and the University of Natural Resources and Life Sciences, Vienna and includes 10 subpopulations, where the assignment of an agent to a subpopulation depends on their socio-economic characteristics. The different utility functions for the 10 subpopulations are shown in Table 3.2.

As data on DRS modes is not available in the travel survey, it is assumed that the DRS driver and rider modes parameters are equivalent to those of the car and rider modes, respectively.

Table 3.2: Mode parameters for subpopulations(own illustration)

Subpop	c_{ride}	c_{car}	c_{pt}	β_{ride}	β_{car}	β_{pt}	β_{walk}	$\beta_{lineSwitch}$	β_{dur}
0	-12.987	0.768	0.124	-0.258	-12.348	-5.594	-11.625	-0.777	12.159
1	-13.056	0.699	0.114	-2.432	-12.463	-5.834	-12.074	-0.832	14.899
2	-13.096	0.659	0.108	0.716	-12.530	-5.974	-12.335	-0.864	12.470
3	-13.140	0.615	0.102	0.766	-12.604	-6.128	-12.622	-0.899	8.365
4	-13.186	0.569	0.095	-4.059	-12.681	-6.288	-12.923	-0.936	9.566
5	-13.230	0.525	0.089	-1.663	-12.754	-6.440	-13.206	-0.970	4.244
6	-13.252	0.503	0.086	-5.897	-12.791	-6.516	-13.350	-0.988	12.478
7	-13.324	0.431	0.075	-3.637	-12.910	-6.765	-13.814	-1.045	5.106
8	-13.364	0.391	0.069	-5.120	-12.976	-6.904	-14.074	-1.077	4.456
9	-13.442	0.313	0.058	-0.974	-13.106	-7.175	-14.580	-1.139	4.692

3.4.2 Network

The Upper Austria scenario covers the province of Upper Austria and certain areas in the southwest of Lower Austria around Amstetten. The simulation uses a network comprising 418,000 links and around 185,500 nodes extracted from open street map (OSM). The network includes PT network as well. Figure 3.6 shows Upper Austria's network.

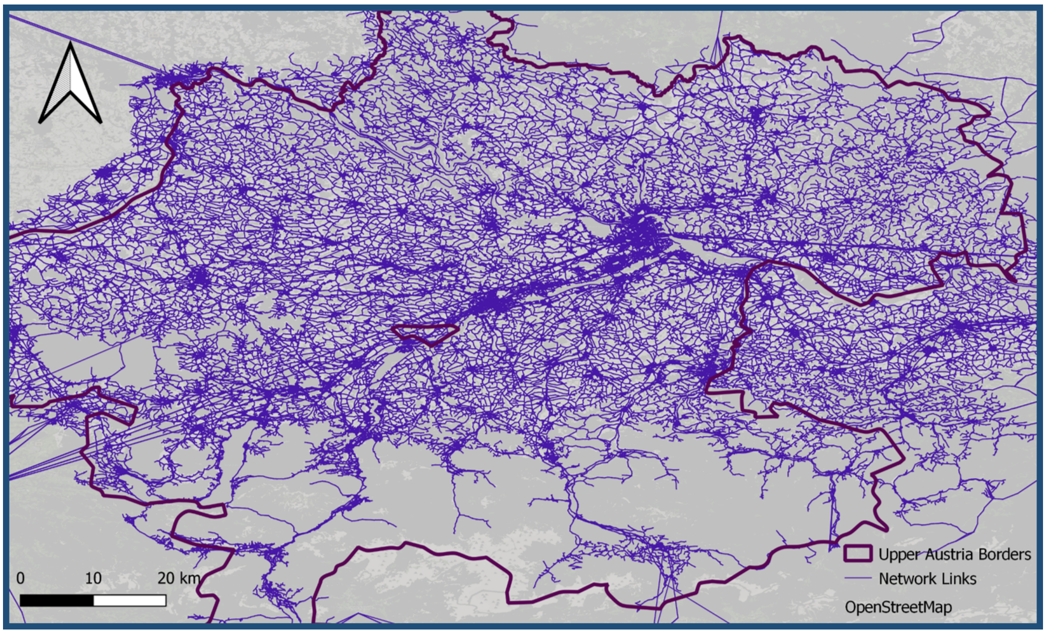

Figure 3.6: Upper Austria's network (OSM)

In addition, approximately 449,950 facilities, including 642 for education, 3,622 for errands, 389,583 for home, 19,478 for leisure, 7,117 for shopping, and 29,508 for work, were also extracted from OSM and the Geostat population density grid (2011). These facilities are available for agents to carry out their activities, such as private/home, work, education, errand, shopping, and leisure.

Furthermore, to enable DRS agents to use the car network in the simulation, and since 'DRSDriver' mode is treated as a separate mode from 'car' mode, "DRSDriver' mode is added as an allowed mode to all car network links.

3.4.3 Configuration

A simulation in MATSim requires numerous configurations. This subsection provides a clear explanation of all the configurations required to utilize the new DRS extension. Table 3.3 shows the required configurations for DRS in MATSim.

Table 3.3: dynamic ride-sharing configuration (own illustration)

module	param name	value
strategy	strategyName	subtourModeChoiceForDRS
qsim	mainMode	car,DRSDriver
plancalcScore	networkModes	car,DRSDriver
	monetaryDistanceRate$_{DRSDriver}$	cost/km excluding profit/km
	dailyMonetaryConstant$_{DRSDriver}$	0
	dailyMonetaryConstant$_{Car}$	0
drs	riderDepartureTimeAdjustment	15 minutes
	maxPossibleCandidates	20
	timeSegmentLength	2 hours
	cellsize	2000m
	carAndDRSDailyMonetaryConstant	-12.34
	driverProfitPerKm	cents/km
	pickupWaitingTime	3 minutes
	unMatchedRiderPenalty	10 EUR

- Subtour Mode Choice for Dynamic Ride-Sharing:

  A new mode innovation strategy called 'subtourModeChoiceForDRS' is created as an adapted version of the MATSim innovation strategy 'subtourModeChoice'. The new strategy adds by default the new DRS modes to the list of modes that can be chosen by agents. In addition to that, it considers the DRS driver mode as a chain-based mode, requiring the same mode to be taken for the return trip to the starting activity. The strategy also checks which agents are eligible to be DRS drivers, only agents with car availability and driving license can be drivers. In addition to that, the new subtour mode choice for DRS has a key feature of initiating all eligible agents to be DRS drivers with a new plan comprising legs with the DRS drive mode. MATSim guarantees to try out and score all un-scored plans of an agent before a different plan is selected. This feature is critical to ensure the presence of a sufficient number of DRS drivers at the beginning of the simulation, thus preventing the "starvation" of individuals who choose the DRS rider mode. *The 'subtourModeChoiceForDRS' strategy has to be added as a new strategy in the strategy module in MATSim.*

- Main Modes and Network Modes:

  In order for MATSim to handle the new DRS driver mode correctly, the new mode DRSDriver has to be added as a main mode in 'qsim' and a network Mode in the 'plancalcscore'.

- Daily Monetary Constant:

  'dailyMonetaryConstant' is a mode parameter in MATSim which refers to the monetary amount an agent pays per day to use a mode. However, since DRS driver and car mode are independent modes, it would be inaccurate to charge an agent twice for both modes in a plan. Thus, it is crucial to set the daily monetary constant for these two modes to zero when using this extension. A new configurable value called 'carAndDRSDailyMonetaryConstant' is included for both modes and utilized by an algorithm to verify the plan of the agents, where any agent who has either DRS driver or car mode would be charged the daily monetary constant only once. *The new configurable 'carAndDRSDailyMonetaryConstant' has to be used instead of the daily monetary constant parameters of DRS driver and car modes.*

- Monetary Distance Rate:

  The 'monetaryDistanceRate' in MATSim is a mode parameter that indicates the monetary rate paid per unit of distance. Incorporating the driver's potential profit in the monetary distance rate of the DRS driver mode within the 'planCalcScore' module could result in inaccurate results because the monetary distance rate for DRS drivers varies depending on whether they have a rider in the car or not. To account for the profit earned by drivers when picking up a rider, a new configurable value called 'driverProfitPerKm' is introduced. This value represents the profit per kilometer earned by the driver when sharing a ride. *Thus, it is essential to configure the monetary distance rate of the DRS driver mode to include the base monetary rate, while accounting for the profit resulting from ride-sharing using the 'driverProfitPerKm' value.*

- Rider Departure Time Adjustment:

  The configurable value 'riderDepartureTimeAdjustment' represents the number of minutes that a DRS rider is willing to adjust their departure time in order to find a matching driver. This value is utilized during the matching process to evaluate whether the driver and the rider have compatible departure times. *Even though agents'* *willingness to adjust their departure time would be different in reality, in the scenarios in this thesis, a value of 15 minutes is used for the departure time adjustment allowed for riders.*

- Maximum Possible Candidates:

  'maxPossibleCandidates' is a configurable value that Limits the number of possible riders requests considered for a driver during the matching process. This is important to speed up computations. *According to the Taxi extension in MATSim, values from 20 to 40 requests make a good trade-off between computational speed and quality of results. For the scenarios in this thesis, a value of 20 is used.*

- Time Segment Length:

  The 'timeSegmentLength' determines the time segment length used to filter riders in the matching process. To avoid scenarios where a driver and a rider departure time are close but cross a segment boundary, riders requests are token not only from the current segment but also from the segment before and after. *In this thesis, a value of 2 hours is used for the time segment length. The purpose of using time segments is mainly to speed up the computations.*

- Cell Size:

  Similar to the 'timeSegmentLength', 'cellSize' determines the side length of the cells created in the grid zonal system that is used in the matching process. The larger the cell size, the more possible matches could happen. *However, it is important to know that an increase in cell size could yield in high detour values in addition to higher computational time. In the scenarios in this thesis, a value of 2000m is used for the cell size.*

- Pickup Waiting Time:

  'pickupWaitingTime' accounts for the amount of minutes the driver is going to wait for in case the rider didn't show up on time. *Even though peoples' willingness to wait would differ from one to the other, in this thesis, a value of 3 minutes is used for the pickup waiting time.*

- UnMatchedRiderPenalty:

  Due to the fact that DRS riders are teleported when a match cannot be found, this could result in higher scores for the DRS rider mode. To address this issue and simulate the inconvenience of not finding a match and having to search for an alternative mode, a penalty is implemented for unmatched riders. This was done to reflect the negative experience associated with DRS rider mode when a suitable match cannot be found. *Even though the perceived inconvenience of not finding a match would vary between people, in this thesis, a value of 10 euros is used as a penalty for unmatched riders.*

3.4.4 Scenarios

In this subsection, we define a range of scenarios that will be simulated using MATSim and its new DRS extension. These scenarios will examine the impact of financial incentives for DRS drivers on the transport system, specifically in terms of mode share and VKT. The scenarios will vary based on the amount of money the DRS drivers receive per kilometer when sharing a ride.

As mentioned in a previous subsection, DRS driver profit/km is configured using the new configurable value 'driverProfitPerKm' in the DRS config group. In this study, in addition to a base scenario without the DRS modes, eight scenarios with eight values used for the financial incentives ranging from 0.1 EUR/km to 0.8 EUR/km. Table 3.4 shows the different values used for the financial incentives given to the DRS drivers.

Table 3.4: Simulation scenarios (own illustration)

driverProfitPerKm							
0.1 EUR	0.2 EUR	0.3 EUR	0.4 EUR	0.5 EUR	0.6 EUR	0.7 EUR	0.8 EUR

4 Results

This section presents the results of the simulations conducted in this study. The section is divided into two parts: simulation performance and scenarios results. The first part presents an evaluation of the computational performance of the simulations and the ability to reach an equilibrium. The second part presents the results of the simulation scenarios, including the impacts of different financial incentives on requests success rate, modal split and vehicle kilometers traveled.

4.1 Simulation performance

4.1.1 Scoring statistics

In a co-evolutionary multi-iteration ABM approach, the accuracy and consistency of results rely on achieving a state of equilibrium in the overall system [50]. This state can be indicated by relevant statistics such as the plan scores of agents. The plans score statistics over iterations for a MATSim simulation with DRS compared to one without DRS are illustrated in Figure 4.1 and Figure 4.2. The figure shows that the DRS scenario reaches equilibrium within 100 iterations, similar to the base scenario.

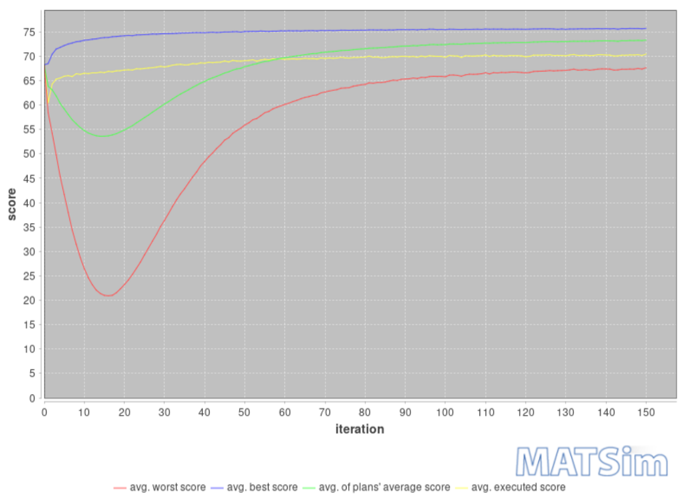

Figure 4.1: Plans scores over iterations for base scenario (MATSim output)

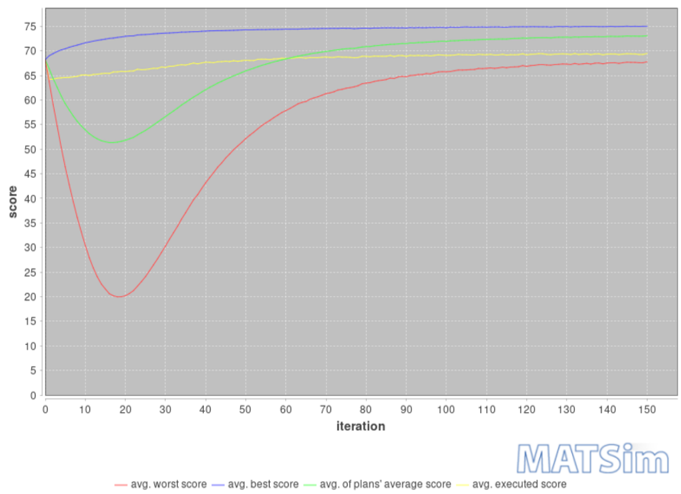

Figure 4.2: Plans scores over iterations for DRS scenario (MATSim output)

4.1.2 Requests statistics

The success rate of rider requests is a useful indicator of equilibrium in the simulation, much like score statistics. When the simulation is in equilibrium, the number of successful ride requests should stabilize and not fluctuate significantly. Figure 4.3 shows the riders requests success rate statistics over iterations for a MATSim simulation with DRS. Towards the end of MATSim's iterations, agents stop their replanning activity, implying that they do not select or experiment with new plans. The depicted figure demonstrates a significant decline in requests around iteration 120 as a result of this phenomenon. Nonetheless, the number of matched requests appears to have reached a state of equilibrium.

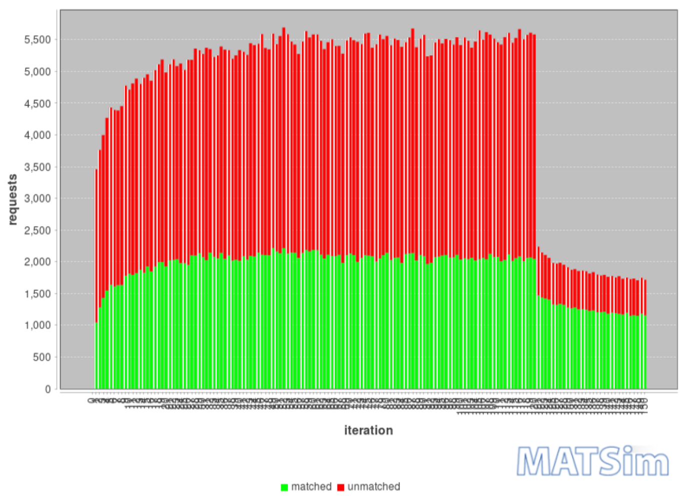

Figure 4.3: Riders requests success rate over iterations (own illustration)

4.1.3 Computational times

In order to assess the computational performance of the new scenarios with the DRS integration compared to the base scenario, the computational time of each simulation was recorded. Figure 4.4 and Figure 4.5 show the computational time for the different steps of MATSim over iterations for a MATSim simulation with DRS compared to a MATSim simulation without DRS. The figure displays a marked rise in the computation time of the iterationStartsListener and qsim in the scenario with DRS when compared to the base scenario. On average, the iterationStartsListener adds an extra 2 minutes per iteration, while mobsim adds an additional minute per iteration.

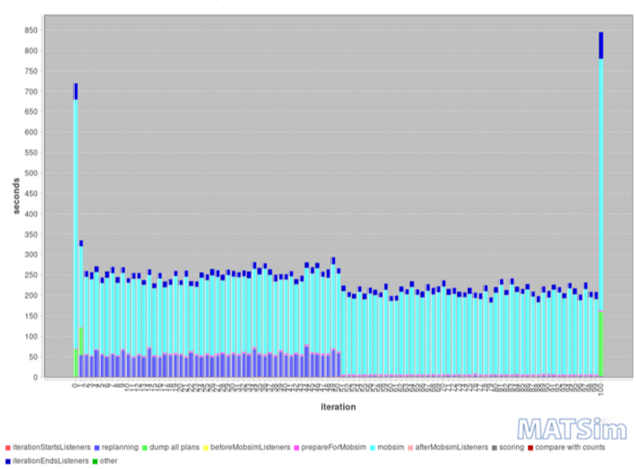

Figure 4.4: Computational times for base scenario (MATSim output)

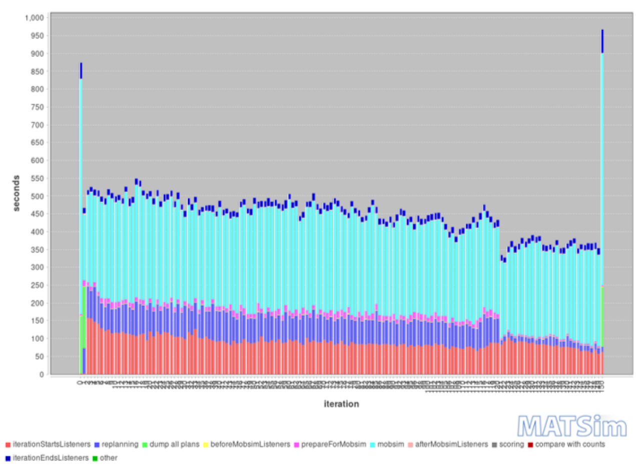

Figure 4.5: Computational times for DRS scenario (MATSim output)

4.2 Scenarios results

4.2.1 Requests success rate

The success rate of requests may serve as a valuable metric to evaluate the efficiency of the DRS system. As shown in Figure 4.6 and Figure 4.7, the success rate of both driver and rider requests is illustrated for the different financial incentive scenarios. As the financial incentives for drivers rise, there is an apparent increase in driver requests with a corresponding slight increase in the success rate that remains within around 3% to 5% range. On the other hand, rider requests also demonstrate a remarkable increase in the number of requests as the financial incentives for drivers increase. Furthermore, the success rate of riders requests is high, ranging from 68% to 78%, for all the scenarios with an average increment of 1% to 2% per 0.1 EUR/km rise in financial incentives for drivers.

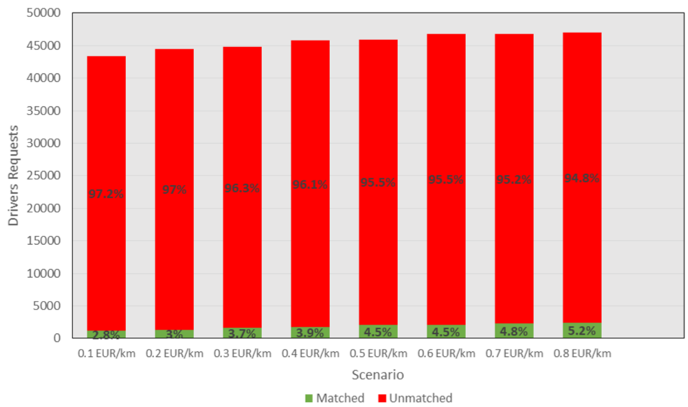

Figure 4.6: Drivers Requests success rate (own illustration)

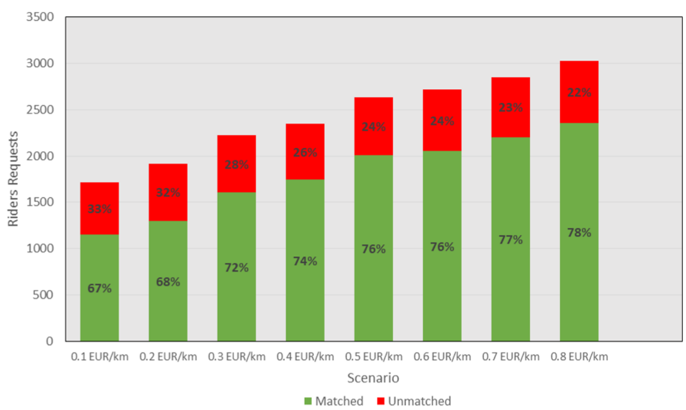

Figure 4.7: Riders Requests success rate (own illustration)

4.2.2 Modal split

Modal split refers to the percentage of trips made by different modes of transportation. The modal split analysis provides valuable insights into the travel behavior of the simulated population. Table 4.1 illustrates the modal split for each scenario, including the base scenario. The results indicate a noticeable rise in the car mode share for all financial incentive scenarios, compared to the base scenario. Conversely, other modes such as walk, bike, ride, and PT depict a decline in mode share for the new scenarios compared to the base scenario. The modal share for all previous modes exhibits slight fluctuations over the financial incentives scenarios, without following a specific trend. Nonetheless, the DRS driver mode share displays an increase with the rise of financial incentives, and so does the DRS rider mode share. Furthermore, DRS unmatched riders indicate a constant value of 0.05%-0.06%.

Table 4.1: Scenarios modal split (Own illustration)

	Walk	Bike	Car	Ride	PT	DRS_{driver}	DRS_{rider}	$\text{DRS}_{unmatchRider}$
Base	16.48%	3.62%	57.78%	15.03%	7.10%	0.00%	0.00%	0.00%
0.1	15.16%	2.93%	59.79%	14.62%	7.24%	0.11%	0.11%	0.05%
0.2	15.13%	2.92%	59.76%	14.64%	7.24%	0.13%	0.13%	0.05%
0.3	15.14%	2.92%	59.71%	14.63%	7.24%	0.15%	0.15%	0.05%
0.4	15.15%	2.91%	59.69%	14.63%	7.24%	0.17%	0.17%	0.05%
0.5	15.14%	2.91%	59.67%	14.63%	7.22%	0.19%	0.19%	0.05%
0.6	15.13%	2.92%	59.67%	14.63%	7.21%	0.20%	0.20%	0.06%
0.7	15.12%	2.90%	59.65%	14.63%	7.24%	0.21%	0.21%	0.06%
0.8	15.12%	2.91%	59.62%	14.65%	7.20%	0.23%	0.23%	0.06%

Based on the mode shares presented, it prompts an investigation to explore the user groups that have shifted to DRS drivers and riders. To visualize this, sankey diagrams have been created for each scenario, as shown in Figure 4.8. These diagrams provide insights into the user groups that are transitioning to DRS drivers and riders, as well as any changes in this pattern across the different scenarios. The sankey diagrams reveal that DRS drivers were mostly initially car users, while about half of the DRS riders were previously using walk and bike modes. Additionally, some DRS riders were previously car users, and a smaller proportion transitioned from PT. Furthermore, the different scenarios didn't show any significant pattern for the modal shifts.

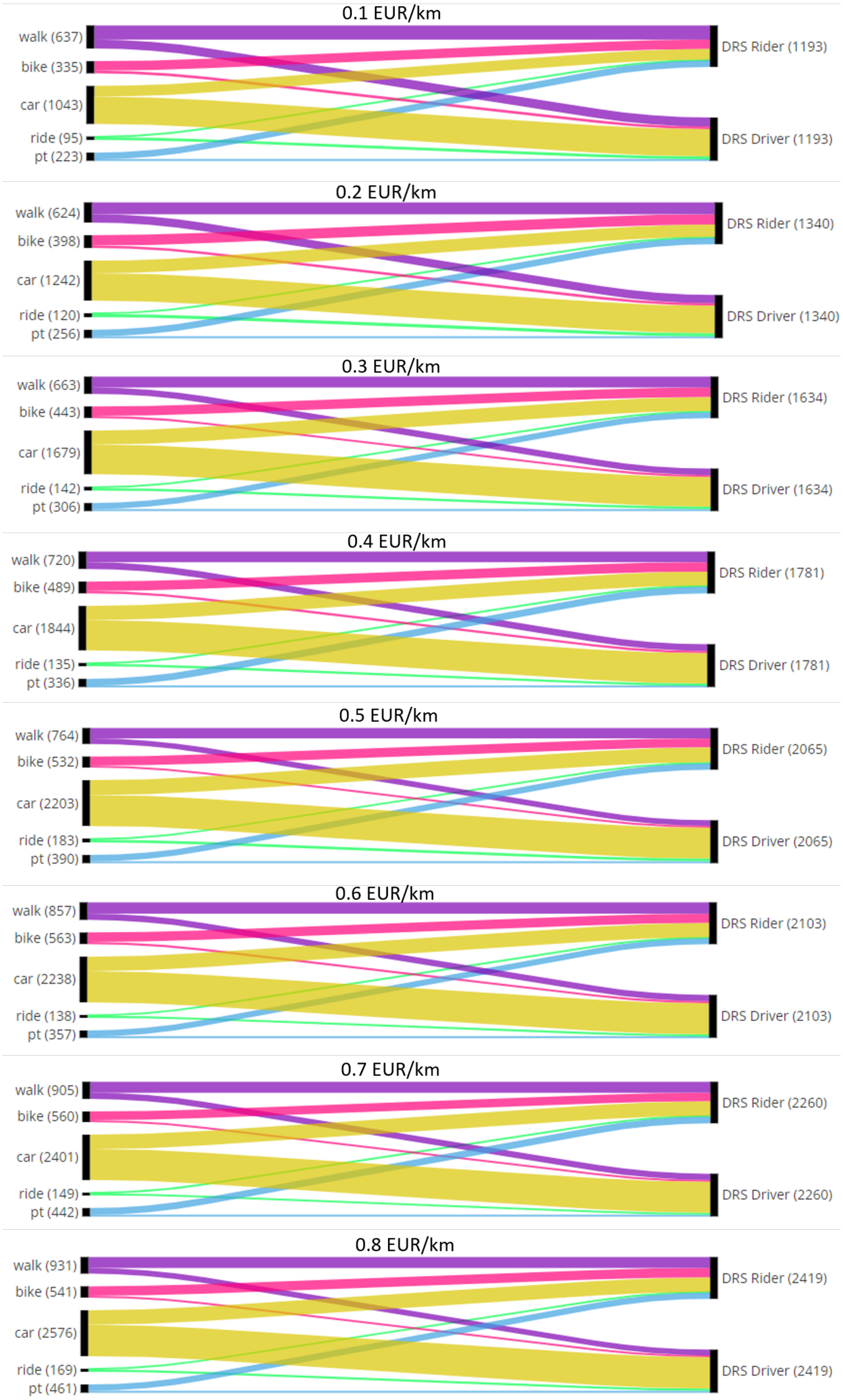

Figure 4.8: Modal shifts to DRS drivers and riders (own illustration)

4.2.3 Vehicle kilometers travelled

Figure 4.9 displays the overall VKT for each scenario compared to the baseline scenario. The figure displays an observed increase of approximately 1.5 million kilometers in the VKT for all scenarios relative to the base scenario. Moreover, the graph shows variability in VKT among the different financial incentive scenarios, without any observable pattern.

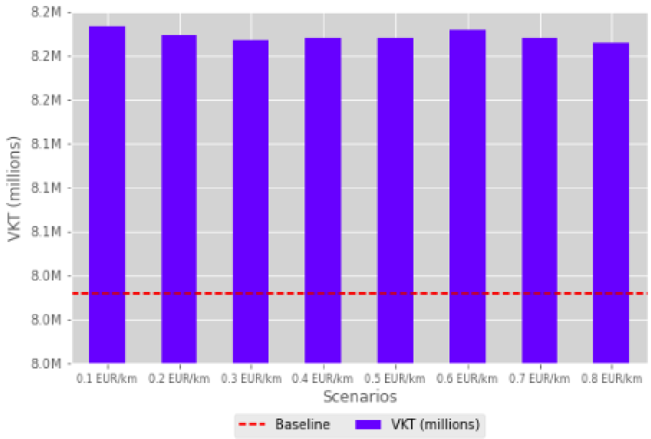

Figure 4.9: Vehicle kilometers travelled for each scenario (own illustration)

Table 4.2 presents the breakdown of VKT for each scenario. Consistent with the earlier findings, shared rides do not make up a significant portion of the total VKT, while individual travel still accounts for the majority. Despite an increase in the shared ride VKT with higher financial incentives, it does not necessarily result in a decrease in the total VKT. The table also indicates that increase ride-shares lead to extra VKT due to the detour to pickup and dropoff riders

Table 4.2: Vehicle kilometers travelled composition for each scenario (own illustration)

Scenario	DRS travel	ToPickup/AfterDropoff	Individual travel
0.1 EUR/km	6125	3055	8183025
0.2 EUR/km	7343	3500	8175811
0.3 EUR/km	10056	4080	8169986
0.4 EUR/km	10421	4557	8170472
0.5 EUR/km	13180	5053	8167351
0.6 EUR/km	11982	5437	8172130
0.7 EUR/km	13794	5740	8165555
0.8 EUR/km	13365	6195	8163020

5 Discussion

5.1 Simulating dynamic ride-sharing in MATSim

- Simulation Equilibrium:

  In real life, people usually try different options before settling on a specific choice. Similarly, in a transportation model, modes of transport are the available options, and agents try to optimize their travel plan by choosing the best option for them. However, the decisions of other agents can affect an agent's own decision. For instance, if an agent is satisfied with a particular PT line, but many other agents start using the same line, it may get overcrowded and impact the agent's decision. Therefore, it is crucial to evaluate the plan scores of agents over iterations and determine whether they reach an equilibrium or not in an agent-based approach. The study's findings indicate that integrating DRS modes will still lead to an equilibrium in agents' plan scores within a reasonable number of iterations, and it is very similar to the baseline scenario without DRS.

  Likewise, an agent's decision to be a DRS rider depends on the availability of other drivers. Thus, the decision-making process in DRS is influenced by other agents' decisions. Therefore, it is crucial to examine whether the number of requests and success rate reaches an equilibrium. Figure 4.3 has illustrated the evolution of the number of requests over iterations. Initially, there is a small and steady increase in the number of requests as new agents try the mode in addition to those who have already used and liked it. Around iteration 120, there is a sharp decrease in the number of requests due to the shut down in innovation strategy where agents don't try new plans anymore and only those who have already used and liked it continue to use it. However, there is a slight decrease in the number of requests after that point because some agents may have other plans in their memory that are better than the DRS rider mode. Towards the end, the number of requests and success rate reaches an equilibrium, indicating that integrating DRS modes can still achieve an equilibrium within a reasonable number of iterations.

- Computational Times:

  The simulations for this study ran on a server with an Intel Xeon CPU E5-2660 v3 @ 2.60 GHz processor and 30 GB RAM. The base scenario with 150 iterations was completed in approximately 12 hours, while the scenarios incorporating DRS took between 19 to 22 hours for simulations with 150 iterations. As shown in Figure 4.5 and discussed in the results section, the increase in run time was mainly occurring at the iterationStartListener and qsim. Knowing that the undoing of plans modification step in DRS utilized the iterationStartListener, while executing the plans was part of qsim, these findings suggest that the algorithms employed to undo plan modifications can be improved further to reduce simulation time. The results also indicate that the matching algorithm used does not consume much computational time, which justifies the use of the single drive- single rider matching approach and suggests that other approaches could be considered and tested for feasibility.

- Success Rate:

  Results showed a low success rate for driver requests, which can be attributed to the small number of riders available for matching. Even if all the available riders were matched, a large number of drivers would remain unmatched due to the high ratio of drivers to riders. However, the success rate for rider requests is shown to be high, reaching around 70% for various scenarios. This value is consistent with other studies that have used different matching algorithms and case studies [51]–[53]. It is important to note that the success rate can vary depending on various factors such as driver to rider ratio, critical mass, population density, and the specific configurations and settings of the matching algorithm. Therefore, the success rate results should be interpreted with consideration of these factors.

5.2 Financial incentives impacts

The central hypothesis of this thesis assumed that offering financial incentives to drivers would reduce DRS by increasing ride sharing, as drivers would be incentivized to share rides and thereby increase the driver-to-rider ratio. This, in turn, would boost the probability of riders finding a match and encourage more people to become riders. The net result would be increased shared rides, improved vehicle occupancy, greater transport efficiency, and ultimately, reduced VKT.

However, the results of this study suggest that the financial incentives attracted not only car users, but also individuals who otherwise might not have used cars to take advantage of the incentives. The findings also show that around 50% of the riders were originally using bike and walking, however the size of the rider pool still remained small, leading to a low success rate for drivers' requests and many new car drivers driving alone without the ability to share a ride.

Despite this, the increase in the number of drivers suggests that individuals tend to continue using cars, even if the benefits are infrequent due to the small pool of riders. Occasionally, they may find a match and receive incentives, but for most of their trip, they end up driving alone. Consequently, the study results indicate an increase in VKT, contrary to the original hypothesis. Figure 5.1 provides a comparison between the hypothesis and the study findings.

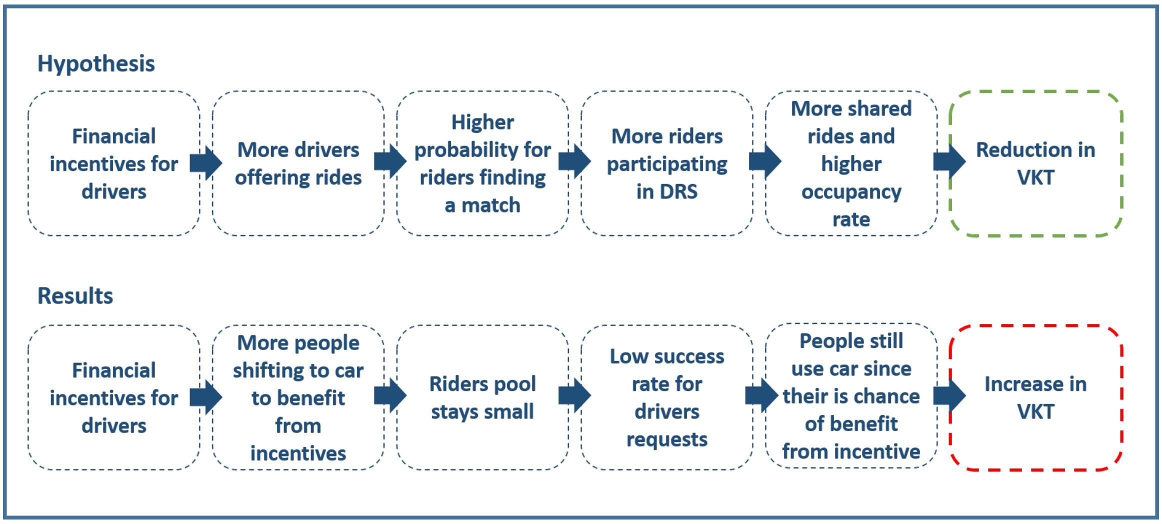

Figure 5.1: Hypothesis vs. Results (own illustration)

6 Conclusion

This thesis has contributed to the field of DRS modeling and simulation. The integration of the behavior of DRS drivers and riders into MATSim provides a powerful tool for testing different scenarios and interventions of DRS within the context of the entire transport system. The thesis has utilized the extension to evaluate the impact of money incentives on people's decision-making and the overall vehicle kilometer traveled. These findings provide valuable insights into the behavior of DRS drivers and riders and can inform the development of more effective policies and interventions to promote sustainable transportation. This work serves as a solid foundation for future studies and applications in the field of DRS modeling and simulation.

The conclusion section of this thesis summarizes the key findings and answers the research questions. In addition to that, it highlights the potential applications of the DRS extension within the MATSim framework, as well as the limitations and areas for future research.

6.1 Lessons Learned

This thesis has explored the possibility of integrating DRS behavior in the MATSim simulation framework. The model was utilized to examine the effect of offering financial incentives to drivers on reducing VKT in Upper Austria. The work attempted to answer the following research questions that were mentioned earlier at the end of the literature review section. The research questions and their answers are as follows:

1) How could the DRS behavior of drivers and riders be modelled in MATSim?

The thesis offers a comprehensive methodology for modelling DRS and outlines the steps involved in integrating it with MATSim. The results suggest that MATSim is a potent tool for modelling DRS, owing to its capability of capturing the spatio-temporal dynamics of the system and providing a holistic approach within the transport system. This opens up various potential applications for future research. Nevertheless, it is important to acknowledge that the extension has certain limitations that need to be addressed through further research to improve the modelling accuracy of DRS.

2) What is the impact of financial incentives for DRS drivers on reducing the VKT?

The study showed that drivers did respond to the incentives by offering rides. However, the incentives also attracted other users to use cars. Furthermore, due to the lack of incentives for riders, drivers only occasionally got matched, leading to an increase in the VKT. It is concluded that financial incentives for drivers alone were not enough to reduce the VKT, and that other push measures such as HOV lanes and increasing fuel costs should also be implemented to encourage the use of DRS.

6.2 Possible Applications

While this study focused on the impact of financial incentives on reducing the VKT, the DRS extension has potential for a wide range of applications. Some examples of potential applications of the DRS extension are as follows:

- Spatial Analysis: The DRS extension offers the possibility of analyzing the relationship between situational factors (such as population density, PT availability, and quality) and the success of DRS services. The extension provides an output that displays the origin-destination (OD) pairs of the DRS trips, including both matched and unmatched trips. By utilizing this output and conducting an analysis of the aforementioned situational factors, it is possible to gain insight into the success of DRS services in different contexts. For example, it is possible to explore whether DRS services are more successful in areas with higher population densities and better PT access. Such applications is useful to identify areas where DRS systems may be particularly effective, as well as areas where additional interventions or improvements may be necessary to encourage greater usage of these services.

- Temporal Analysis: A promising application of the DRS extension is the implementation of demand-responsive financial incentives. Such incentives can be easily incorporated into the extension and can be used to analyze the impact of financial incentives on the number of vehicles on the network during peak hours. By examining the resulting changes in the number of single-occupancy vehicles on the roadways and the corresponding increase in the number of shared rides, this type of analysis can provide valuable insights into the effectiveness of demand responsive financial incentives as a tool to promote DRS usage and reduce congestion during peak hours.

- Trip Purpose Analysis: The output generated by the DRS extension also includes the type of activity associated with each destination of the DRS trips. This information can be used to analyze the distribution of trip purposes for DRS riders and drivers, shedding light on the most common and rare trip purposes. Such an analysis can provide insights into the behavior of DRS agents and inform the development of interventions that are more likely to be effective in promoting the adoption of DRS.

- Trip Length and Duration Analysis: Studying the trip length and duration of shared rides is another important area of analysis. By examining these factors, we can gain insight into the preferences and behaviors of users in terms of intra-city and inter-city trips. For instance, if users tend to prefer shorter intra-city trips, we may need to design incentives that are more appealing for such trips. Similarly, if users prefer longer inter-city trips, we may need to offer different incentives to encourage more shared rides on those routes.

- Equity Analysis: DRS extension can also be used for equity analysis. By analyzing the characteristics of the DRS agents such as their socio-economic status and location, the extension can provide insight into the potential equity impacts of dynamic ride-sharing interventions. For example, the extension could evaluate whether DRS interventions would disproportionately benefit or burden certain groups of people, such as low-income individuals or those living in areas with limited PT options.

6.3 Limitations

Despite the promising results and potential applications of the DRS extension within MATSim, there are also several limitations that should be acknowledged. These limitations are important to consider in order to understand the scope and generalizability of the findings, as well as to guide future research in improving the extension. Some of the limitations are stated below:

- Single Driver and Rider Matching: One limitation of the DRS extension is the fact that it only allows for one rider to be matched with one driver at a time. This means that the potential for ride-sharing is limited, and the full potential of the DRS system may not be realized. The extension does not account for the possibility of multiple riders being matched with a single driver. This limitation could impact the effectiveness of the DRS system in reducing congestion and emissions, as it limits the number of vehicles that can be taken off the road. Additionally, it may limit the economic benefits of ride-sharing for both drivers and riders, as the cost savings of sharing a ride may not be fully realized.

- Before Day Start Matching: For the purpose of modeling, collecting requests before the day starts may not significantly impact the results compared to collecting requests dynamically. However, it should be noted that this approach does not reflect the actual operation of a DRS service and may not be practical for real-world implementations. Collecting requests and matching dynamically could be more appropriate for scenarios involving autonomous vehicles, where requests can be generated and matched in real-time based on the vehicle's location and availability.

- Door to Door Service: The DRS extension implemented in this study assumes a door-to-door service, where the driver picks up and drops off the rider at their respective origins and destinations. However, this approach may have some limitations in terms of efficiency and service quality. A stop-based system, where riders walk to designated pickup and dropoff points, could potentially reduce travel time and improve system performance. However, implementing such a system would require routing algorithms to efficiently allocate riders to stops, as well as considerations for accessibility and convenience for riders. Further research could explore the trade-offs between door-to-door and stop-based systems and develop efficient routing algorithms to improve the overall performance.

- Teleportation Instead of Picking Another Mode: One limitation of the DRS extension is the approach taken to handle unmatched riders, where they are teleported to their destination instead of choosing an alternative mode of transportation. While this approach simplifies the modeling process, it is not reflective of real-world scenarios where riders have other options available to them in case of not finding a match. The downside of teleportation is that it can affect the accuracy of the results as it assumes that the rider would not use an alternative mode of transportation, leading to potentially inaccurate statistics.

- Sociodemographics in Matching Process: Another limitation of the DRS extension is that matching is solely based on distance and time, without taking into account sociodemographic factors. In reality, riders and drivers may have preferences for matching based on their sociodemographic characteristics, such as age, gender, or profession. Future extensions could consider incorporating sociodemographic factors into the matching process to improve the accuracy and realism of the model.

6.4 Future Research

This thesis represents an important milestone in the integration of DRS in MATSim. While the research has yielded valuable insights into the possibility of integrating DRS in MATSim, there is still much room for further development and future research since the DRS extension is still in its early stages of development. Below are some potential areas of future research that could build upon this thesis work. Additionally, Table 6.1 provides a summary of potential future work based on the limitations and future research section.

- Mode Choice Model Including DRS Modes: This study made an assumption that the mode parameters of DRS drivers and riders is similar to that 'car' and 'rider' modes, respectively. This was done because there was no available data to estimate the mode parameters of the new DRS modes. Although this assumption simplifies the modeling process, it may lead to some inaccuracies in the results. To improve the accuracy of the model, future studies can address this issue and estimate a mode choice model that includes these new modes.

- Cell Size: The cell size of 2000 used in this thesis work was chosen as a trade-off between system efficiency and computational power. However, it is worthwhile for future studies to investigate the impact of the cell size value on the number of matches and the resulting detour. It would also be interesting to explore whether different cell sizes should be used in different urban contexts, given that the optimal cell size may vary depending on the density and layout of the road network. By addressing these questions, future studies can provide insights into the optimal range of cell size for different contexts, which can lead to more accurate models and results.

- Unmatched Rider Penalty: As noted in previous sections, unmatched riders in the simulation are teleported and given a penalty to reflect the inconvenience of not finding a match. In this study, a penalty of 10 euros was applied to unmatched riders. A small penalty may not be significant enough to discourage agents from using the rider mode even after experiencing difficulty finding a match. Conversely, a high penalty can disproportionately affect an agent's plan if they have multiple legs of the rider mode, with only one leg being unmatched. Therefore, further research is needed to determine the optimal penalty that can effectively discourage the use of DRS rider mode without disproportionately impacting the overall plan score.

- Rider Departure Time Adjustment: In this thesis, DRS riders were given the option to adjust their departure time up to 15 minutes to increase their chances of finding a match with other DRS drivers. However, this value was arbitrarily chosen and requires further investigation. Future studies could gather information on the willingness of agents from different sociodemographic backgrounds to modify their departure time. This would enable the identification of the appropriate value that reflects the readiness of agents to adjust their departure time based on sociodemographic variables. As a result, the DRS model could achieve a more precise representation of travel behavior.

- Pickup Waiting Time: Similar to the departure time adjustment, maximum waiting time for drivers to at pickup point was arbitrarily chosen in this thesis. Further studies are needed to explore different waiting time values for different sociodemographic groups. This can improve our understanding of the willingness of drivers to wait and lead to more accurate modeling of dynamic ride-sharing systems.

Table 6.1: Potential areas for future research (own illustration)

Potential Future Research
Multiple riders and drivers matching algorithm
Dynamic matching
Door to door DRS
Picking another mode when unmatched
Sociodemographic preferences in matching process
DRS parameters estimation
Cell size configuration
Unmatched rider penalty configuration
Rider departure time adjustment configuration
Driver pickup waiting time configuration

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