Title

Modeling the interactions of price-cost-ownership paradigms with traveler usage patterns and system performance in new shared autonomous mobility systems

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Modeling the interactions of price-cost-ownership paradigms with traveler usage patterns and system performance in new shared autonomous mobility systems

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Eduardo Mariño Fernández

Dissertation Committee:
Professor R. Jayakrishnan, Chair
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2022

DEDICATION

To

my parents

Cecilia Fernández and Eduardo Mariño

my sisters

Pimpo and Ana Gabriela

and

all the friends and family that have supported me in this journey

It would not have been possible without you

"¿Qué es la vida? Una ilusión,
una sombra, una ficción,
y el mayor bien es pequeño:
que toda la vida es sueño,
y los sueños, sueños son."

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ABSTRACT OF THE DISSERTATION

Modeling the interactions of price-cost-ownership paradigms with traveler usage patterns and system performance in new shared autonomous mobility systems

by

Eduardo Mariño Fernández

Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2022

Professor R. Jayakrishnan, Chair

Mobility systems are undergoing a major transformation due to emerging autonomous and shared mobility technologies. A primary aspect of such technologies is improving the mobility system inefficiencies via a reduction in the number of vehicles needed to fulfill the transportation needs. This would impact the use of vehicles and their expected lifetime. This dissertation is focused on the importance of the increased usage of vehicles and how the system can benefit from an optimization with a vehicle point of view.

The improvements come from mainly two aspects of shared mobility – carsharing and ridesharing – which are both implemented in the modeling and optimization framework. An analysis of the current vehicle ownership and trip distributions is presented. A vehicle usage cost function is designed to incorporate the changed relative importance of fixed and usage-based variable costs. It presents a framework that analyzes the interactions between all the elements, including a pricing scheme for benefit-cost analysis and optimizations from a service provider perspective.

With shared mobility, ownership paradigms can also change to subscription-based use of vehicles from fleet service providers, as included implicitly in the interaction framework. Modeling is carried out for idealized networks, as well as a real-world network of a reasonable size from the city of Irvine, CA. The results capture the increased use of shared and/or autonomous vehicles and the benefits of optimizing the system with properly updated costs. Results and conclusions are provided on the viability of service provider plans as well as on system benefits in terms of the replacement ratio indicating how many personal vehicles can be removed using autonomous fleets.

CHAPTER1:
Introduction

Motivation

Transportation is currently undergoing three major transformations: electrification, shared and on-demand mobility, and automation (Sperling, 2018). These are presented as the future of transportation, which will solve current problems of congestion, safety, and pollution; however, they also represent a new set of challenges and impacts on the transportation system and should be analyzed (Sheppard et al., 2019).

These transformations are changing the way transportation is envisioned with new possible systems and mode combinations (microtransit, autonomous vehicles (AVs), fleets of vehicles or mobility portfolios); new mobility situations where vehicles are shared between the users (fleets of autonomous vehicles); and even new ownership paradigms where the user is no longer the owner of the vehicle and only pays for the time that he uses the vehicle.

Current cost and objective functions are not sufficiently sophisticated for the kind of changes that are possible in the near future and do not consider the implications of the interactions between the new transportation paradigms. In this research we analyze some of the problems of the current situation, study the use of ridesharing systems as a solution, along with how they present new challenges, especially in terms of increase mileage in a smaller time span, and we focus on how we can analyze them and optimize a mobility system with agent-based simulation and proper cost functions.

We consider the importance of these future scenarios and the use of subscription service concepts such as mobility portfolios developed at UC Irvine (An, 2019) to manage the different modes and services. We study the impact of increasing the number of shared vehicles and state the basis on how we can analyze their cost. This will be used to simulate different scenarios in which we will be able to consider subscription services serving the demand of a network, to analyze their interactions and different transportation modes, including shared and/or autonomous vehicles. The final step would be to be able to analyze the impact of including bigger fleets of SAVs to serve the demand in an area, and how we can consider the cost of these fleets in a more individualized way.

Research has shown that cars are known to be parked 95% of the time (Shoup, 2005). This value, added to the low seat utilization rate, represents a vehicle efficiency rate lower than 4%. (i.e., cars are used only about 1/6th of the productive time they can be used, and only about 1/4th of the seats are used as well, resulting in 1/24 efficiency). Hence, the most used mode of transportation is known to be very inefficient, as it causes significant congestion and harmful vehicle emissions, yet it still plays a major role in people's life and expenses.

The new transformations are expected to solve some of these problems. As shown in some studies such as by Sheppard et al., 2019, the full level of current mobility in the United States (US) could be achieved by only 12.5 million Shared Autonomous Vehicles (SAVs) at a much lower cost. That number could potentially be very much underestimated, but it is quite evident that significant reductions in the number of vehicles are possible with newer paradigms of usage and ownership.

The aim of this study is to present a framework to analyze the comprehensive modeling of interactions between demand, supply, and performance, to arrive at more reliable estimates. Of special interest is how we should analyze the importance of costs in new transportation systems and how these changes could affect ownership and usage patterns. To meet this goal, we analyze the current situation and simulate the increased use of vehicles in shared mobility scenarios. Then, we implement a more specific cost function for each vehicle of the system to consider the new challenges that appear. Finally, we analyze the interaction of supply and demand in subscription systems and present situations where we can better optimize the mobility system.

We finish this chapter with the background needed, and in the following sections we describe the transportation costs and variables; the framework of the simulation, with the methodology proposed, a test simulation, and the different possibilities of implementation; future scenarios considered of SAVs; and the conclusions of the dissertation.

Background

Current situation

Transportation has an important role in people's lives, not only in terms of conditioning the actions that they can do, but also in the amount of money that has to be invested in order to have a proper level of mobility. The economic impact of transportation varies a lot from one person to another and from one country to another, so here we present the current situation for the case of the US. The question is, how significant is transportation in terms of its cost impacts in the US?

According to the Bureau of Transportation Statistics, the United States invested in 2017 about 8.8% of the GDP (Gross Domestic Product), which is approximately $1.7 B. This percentage hasn't changed much in the recent years and represents even more money than channeled to education (6.6% of GDP) (Figure 1).

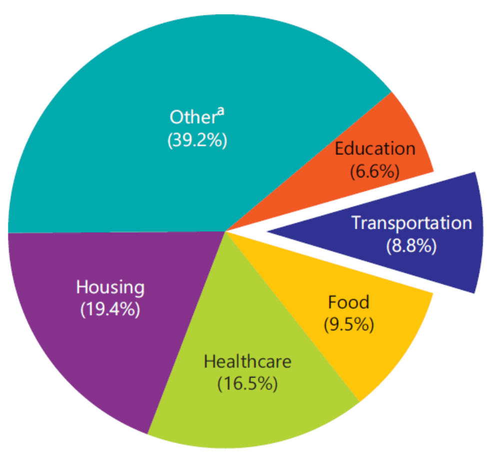

Figure 1. US GDP spending category (Bureau of transportation statistics, 2017)

However, transportation costs are not just from government investments; it also represents an important component in the average annual household expenses of the people. This is about $9600, in which the purchase of the vehicle is the highest fraction, at around the 42% of the expenses.

Even with these high investments and costs, people certainly continue to want to be mobile, and transportation costs are considered unavoidable. Nonetheless, during the past several decades, we can see a trend where individual vehicle usage is becoming more prevalent and transit ridership has been declining. In, Figure 2 we can see how the total number of trips using transit is in a descending trend, whereas the total number of vehicle-miles traveled (VMT) is increasing. If we analyze the global commute share of workers, we can see how driving alone using a personal vehicle is the mode with the highest representation (more than 75%).

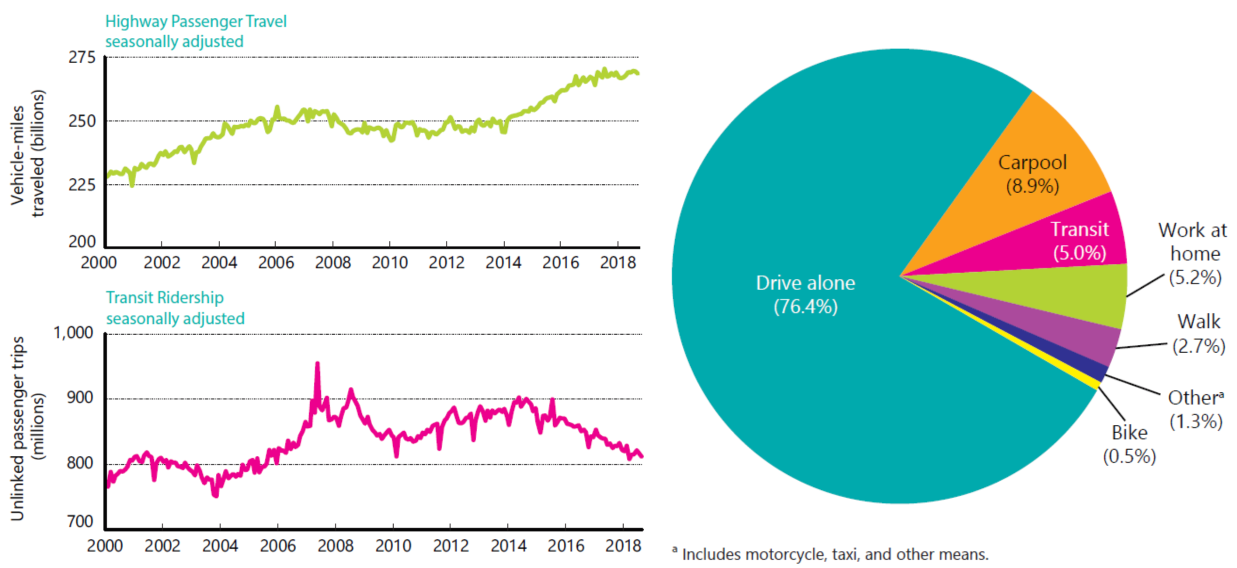

Figure 2. Comparison of travel trends between highway travel and transit ridership (Bureau of Transportation Statistics, 2017)

About 85% of the American workers use the car for their commute every day. Such individual mobility is served by over 275 million personally owned vehicles (Sheppard, 2019) and according to the Bureau of Transportation Statistics, the typical auto commuter spends 25.7 minutes driving to work. Given the current infrastructure, this generates heavy congestion, causing the American driver to lose on average 42 hours every year, stuck in traffic, which represents a delay cost of at least $1000 per person each year, which is also more than 1.5% of the income per capita.

More interestingly, research has shown that cars are known to be parked 95% of the time (Shoup, UCLA, 2005), which added to the low seat usage causes an efficiency lower than 4%, as we can quickly calculate (i.e., cars are used only about 1/6th of the productive time they can be used, as in say the peak hours when high mobility demand, and only about 1/4th of the seats are used as well, resulting in 1/24 efficiency). Hence, the most used mode of transportation is known to be very inefficient, cause important costs in congestion and pollution, but still plays the major role in people's life and expenses.

The new transformations are expected to solve some of these problems. As shown in some studies such as by Sheppard, 2019, the full level of current mobility in the United States could be achieved with only 12.5 million Shared Autonomous Vehicles at a much lower cost. That number could potentially be very much underestimated, but it is quite evident that significant reduction in the number of vehicles is possible with newer paradigms of usage and ownership. Comprehensive modeling of interactions between demand, supply, and performance, as intended in this dissertation research, is needed to arrive at more reliable estimates. But at the same time, considering all of the new interactions will add new challenges that we will consider in this research. Of special interest is how we should analyze the importance of costs in new transportation systems and how these changes could affect ownership and usage patterns.

Shared and/or Autonomous Vehicles

Automation is one of the three major transformations that are affecting the transportation sector, and among the three it is the one that has been receiving more public attention in recent years. However, most of the times we have the three transformations interconnected. From purely a technology standpoint, the relation between electrification and autonomy may be more apparent, however the full benefit of automation and avoidance of deadhead movements of automated vehicles can be reaped only with shared mobility (both car-sharing and ride-sharing). In this research we focus on the analysis of impacts of new shared and autonomous systems, and how they can bring about an increase on the efficiency of the system and efficient usage of the vehicles. A full study on the impact of electrification, especially as it requires modeling the life-cycle costs of different energy sources, is beyond the research scope.

Sharing economy, also known as collaborative consumption, focuses on the benefits obtained from sharing resources. It is especially important in this research because of the efficiency benefits it can bring in. In particular, we can foresee Transportation Network Companies (TNCs) using private vehicle owners and their personal vehicles to provide flexible and on-demand transportation services. This substantially reduces the cost of capital and human resources, while generating revenue for both the company and the drivers. We study their implications, as they will most probably cause an increase in usage and change of ownership patterns and draw insights on how this would interact with the new cost paradigms.

Autonomous technology can be used in different modes such as cars, buses, or trucks. Cars received more initial attention as the prototype tests were done with them, though trucking is also receiving attention now, thanks to efficiency from platooning and drivetrain characteristics. Autonomous cars, also known as driverless or self-driving cars, are vehicles capable of fulfilling the transportation abilities of a traditional personal vehicles without the humans guiding the system. This can yield several benefits for the transportation and the society: safety by reducing the number of accidents; efficiency by optimizing the number of vehicles on the road; or mobility, especially for people that cannot drive by themselves or that have any disability.

A single AV can be accessible to many more people than currently served by personal autos. They have the potential to reduce ownership costs for users. As vehicles can be used for multiple users after the trips of each, SAVs will show increased availability compared to conventional vehicles, which means that each SAV has the potential to replace several single driver vehicle trips (Gurumurthy and Kockelman, 2018) and increase the occupancy of vehicles through ridesharing, as the vehicles can route themselves to more travelers' locations. In some cases, car ownership rate could drop by even up to 43%, providing more opportunities for a single mode to be accessible to multiple people (Schoettle and Sivak, 2015).

Autonomous capabilities can be used to reduce the need to own multiple vehicles (Mahmassani, 2016), and it could even preclude individual ownership in favor of shared mobility fleets (Fagnant, 2015). Autonomous vehicles can also be used for a better optimization in terms of a shared environment, which is the basis of our study. Travelers will react to these systems based on the benefits from them. Thus, we require proper modeling and cost analysis tools to capture the interactions and evaluate the impacts in the change of usage and ownership of vehicles.

Change of ownership and increase of usage

In this dissertation, the focus is on modeling the above-mentioned new transportation options and how they would interact with the mobility systems and the demand; how they could affect the usage of vehicles and the importance of considering a change of ownership paradigm affecting all together. There is a great deal of uncertainty about how AVs will be implemented and what their impacts will be in the transportation systems in the coming decades; however, there is little doubt that they will be a part of the transportation system at some point in the foreseeable future, and that they could disrupt the conventional modes of mobility.

Autonomous vehicles should replace personal vehicles only in a judicious manner. If their implementation is done by replacing each conventional personal vehicle with an AV, we will keep the same number of vehicles and nothing much would be achieved. It is true that efficiency and security could increase. The time spent inside the car could be used more efficiently too; however, it has been observed in past modeling efforts that the total number of miles driven could significatively increase. With that, congestion could also grow, and in a similar way the level of pollution can also worsen (Bosch, 2018). Notice, however, that market mechanisms will dictate the replacement of personal vehicles with autonomous vehicles, and this will in turn be dictated by cost considerations and optimizations done by the vehicle suppliers and owners – a interaction that needs to be modelled to at least some level of acceptability, as will be attempted in this research.

The increased use of smartphone-enabled technology regarding shared mobility services through TNCs such as Uber or Lyft are possibly already helping in reducing the number of private vehicles. A much higher efficiency could be obtained if we switch the ownership scheme from the users to public/private companies (Sheppard, 2019). There is a wide variety of business models that could make use of AVs, and their success will depend on their relative cost structures, policy regulation, consumer acceptance, and a group of other factors (Bosch, 2018). Shared automated electric vehicles could offer on-demand transportation in electric and self-driving cars similar to the service provided by current TNCs but likely at much lower cost and carbon intensity (Chen, 2016)

Hence, the objective of this change of ownership is to make use of a more efficient system, where the total number of vehicles used will be substantially reduced. In order to keep the same level of service, these fleets of autonomous vehicles would be used much more than conventional cars and current cost models are not prepared for this new scenario. Most of the models used are based only on average costs considering vehicles with an annual average of 15,000 miles and a total life use of 200,000 miles. Our research focuses on analyzing the impact of a much higher use of cars and how to prepare a cost function that considers better these changes.

It is also important to mention that another purpose of this research is to analyze how the disruption caused by these new systems will affect the current situation. New patterns would create a new status where their implementation will depend on how well people react to these changes and accepts them. At the same time, the relationship between costs and demand will also be affected. It is important to consider these relationships, how the new patterns appear, and with them new costs and new demands, (i.e., if new systems such as rideshare or carshare become more prevalent, they will impact the cost of the vehicles, like more money for maintenance, this will impact the possible demand, which will affect again how people react to the new systems).

Transportation cost functions

Having described the main qualitative aspects of the new transportation options under study, we should understand how to analyze it. The most common way to consider its effects is to analyze the benefits that we obtain from it and the costs that they represent. For that purpose, transportation cost functions can be used and the trade-off between resources analyzed. Any cost can be viewed as the reduction in benefits, and the same way, a benefit can be defined as the reduction of a cost. This can involve money, time, land or even an opportunity. Such cost functions determine how much travel can be accomplished and at what costs and prices, depending on the different vehicle types and modes considered. Here we will introduce the cost functions for transportation, as they will be the basis of the optimization for the new mobility systems, and also because they will be the basis of our analysis of the interactions between the cost paradigms and the usage patterns.

These functions summarize information about the mobility situation. Their ultimate purpose is to be the objective function of the system and optimize it to get the best situation (usually highest benefit economic or social) while maintaining a good level of service; and also, to see the effects of changes in the system, such as the needs or the possible impacts of subsidizes in the different modes of transportation, or the application of other factors in the costs, price structures and alternative forms of organization.

The clearest example is one of the most important issues in transportation, namely, congestion. As it can be quantified, a certain amount of congestion may be acceptable just like any other cost; but in any context, we must consider the cost needed to eliminate it or reduce it to an acceptable level. What would be this acceptable level? Naturally, this will be the level at which the magnitude of the cost of congestion does not restrain the system of transportation in the area.

Usually, the most common way of optimizing a transportation system is to minimize the cost of producing passenger trips, and this is done by considering the travel time and the operational cost as the main costs. The former can be fixed or dynamically updated depending on the congestion situation; but the latter can incorporate different parameters. It, however, still needs to consider all the costs during the life of a car. The element with a higher impact is the cost of the driver, something that should not be that important anymore with SAVs (though it could still be important if we consider an operator controlling some parts of operations of some or all the vehicles from a control room, but still much less as the operators required would be much less than the drivers).

The cost function for public transport

The most common approach considers the accounting costs, which seeks to determine the relationship between cost and the intermediate outputs and is usually a linear function of a few measures of intermediate outputs considering elements such as the route miles (RM), the number of peak vehicles (PV), vehicle-hours (VH) and vehicle-miles (VM); as the most important factors that will affect the cost and the minimum cost of producing passenger trips. Thus, the formulation usually has the following form:

$$C = c_1 \cdot RM + c_2 \cdot PV + c_3 \cdot VH + c_4 \cdot VM$$

This formulation can also be modified in order to consider the differences (or balance) between peak and off-peak hours, especially to consider the larger number of vehicles needed for peak hours and the extra costs for the additional service for the drivers during that time of the day. As we can see (Figure 3), there are several examples that take into account this type of cost functions, such as Allport (1981) which analyzes the costs of three types of transit of a single agency; and Boyd, Asher and Weltzer (1973 and 1978), which provide a more representative sample of the bus systems, comparing costs from many transit agencies in Canada, the US and Mexico.

	Rapid rail		Light rail	Bus	
	Boyd[a]	Allport[b]	Allport	Allport	Boyd
Capital cost:[c]					
Per route-mile ($M/yr)	6.57	3.84	0.77	NA	0.99[d]
Per peak vehicle ($K/yr)	104.1	63.2	83.9	16.0	28.4
Operating cost:					
Per route-mile ($M/year)	0	0.920	0.231	0.009	0
Per peak vehicle ($K/yr)	0	63.9	45.2	29.2	0
Per convoy-hour[e] ($)	7.92	41.59	54.55	52.35	30.07
Per vehicle-mile[e] ($)	8.15	2.95	3.12	1.39	1.32

Figure 3. Cost function for public transit (Small, 2007)

Other types of cost functions consider engineering costs, which seek all the characteristics of each mode and the prices for all components to construct the function (Meyer, Kain and Wohl, 1965); or statistical costs, which pool information from different transit agencies to estimate the parameters of the cost functions (Viton, 1980). Most of these studies obtain a U-shaped cost function that can be used to determine the optimal fleet size of the mode. One last aspect consists of adding the user's time as part of the inputs to produce the final output of the total trips. It is found in several studies that economies of density appear in public transportation modes, as waiting time is considered part of the cost. This means that the average user is better off when ridership increases (more routes and higher fleet size).

Even if the focus of this dissertation is on private vehicles, the above studies represent an important resource to explain different ways to obtain cost functions, and the importance of considering the waiting time as a significant aspect to reduce the cost of the system.

The cost function for private vehicles

Automobiles have had for a long time a big impact in people's mobility and in the resulting urban travel patterns. Measuring the cost functions for motor vehicles on highways can help us understand the costs that they represent, and to facilitate pricing and investment. The aim of this work is to focus on new mobility scenarios with shared or autonomous vehicles and consider fleets of autonomous vehicles serving certain demand in a network. Thus, understanding the possible cost functions associated with automobiles can help to understand the variables and relations needed.

The most important aspect associated with the cost function for motor vehicles is the incorporation of user time as a cost, which makes the congestion itself an important issue to determine the number of trips that can be generated and the level of service for each situation. The most common definition of congestion is the situation that occurs when the quality of service of a facility is affected by the intensity of the use, and this impacts aspects in transportation such as the expected travel time, the reliability, and the convenience of the travel. This congestion can arise from different causes including signals, cars entering from side streets or cars following slower vehicles. Consequently, many distinct approaches can be used to analyze congestion.

A common method to analyze the congestion is the use of a fundamental diagram, which gives the relationship between the three main variables that describe vehicular traffic (though this relationship may apply to general transportation flows too):

$$V = S \cdot D$$

Where V is the traffic flow, S is the average speed, and D is the vehicle density.

The relationship presented gives instantaneous information, which sometimes is not useful by itself for an economic analysis of congestion. However, it has many implications in transportation in general, especially in considering the impact in the travel time costs and the implications from the increased use of vehicles in more detail. In order to analyze effects related to the number of people travelling, we can use many travel time functions that are based on the flow of vehicles, as described next.

We can see in Figure 4 the representation of some of the relationships between the flow and the speed. Cost functions make use of average values and will be important in our research to consider an appropriate function cost in the new price-cost-ownership paradigm, and the effect of travel time in different scenarios of new mobility systems.

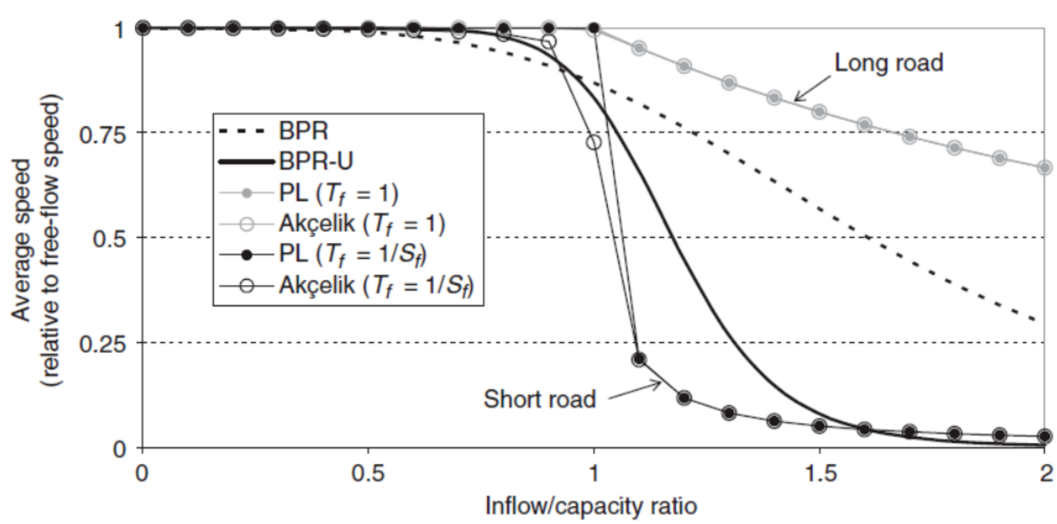

Figure 4. Flow and travel time for different congestion models (Small, 2007)

Cost variables

We have seen how we can analyze the cost of a mode of transportation by understanding their main features and generating a function that can be used to optimize their performance. This function is mainly based in the travel time of the vehicles in the system or a generalized cost of the of operations. However, there is increasing recognition that urban transportation planning should consider a broader range of variables, and not just the travel time, with the objective of better evaluating the costs and benefits.

The way that we distribute and perceive a cost will affect transportation decisions. On the one hand, in general, the consumers are most affected but their costs are internal, direct, and short term. On the other hand, agencies tend to focus more on direct market costs, as they are easier to measure. In the end, external, long term and indirect costs tend to be undervalued. However, many costs of driving have some of these last attributes, which are not considered much in transportation decisions, resulting in economic inefficiency. Thus, we should pay special attention when analyzing transportation costs (Litman, 1997).

There are several applications for this type of analysis but the most important is that by knowing the cost of each transportation system we are able to generate an adequate service that can fulfill the users' travel desires and at the same time be acceptably efficient. But also, by analyzing the cost we are able to adapt to changes generated by the emergence of new technologies that can disrupt the current transportation situation that has many impacts, not only in terms of congestion but also pollution. The current transportation scenario involves many problems that already impacts the lives of people. It is important for new systems to not make the situation worse. Through analyzing the costs derived for the new systems, we would be able to address how these changes will affect the people and adapt the systems properly before the new paradigms substitutes the current ones and cause the same or worse problems.

Another important consideration is that we would be able to develop better transportation policies and conduct better planning by analyzing the transportation costs. We can also analyze different possible scenarios and obtain the best cost-effective solution; the greatest overall benefit; optimal pricing strategies to reflect full marginal costs (incremental cost obtained by adding an additional unit of consumption); and the possible economic development impacts which refer to the progress towards economic goals that benefit the community.

There are many studies that have attempted to evaluate partial or full transportation costs such as Apogee Research, 1994; IBI Group, 1995; European Conference of Ministers of Transport (ECMT), 1998; Van den Bossche et al., 2003; Litman, 1997, 2009; Small, 2007. Here we comment the last two as are the ones that seemed to be more extended in terms of personal vehicles' costs.

Litman in 1997 presented an analysis of these costs for different modes of transportation. As we can see in the following figure, there is already an estimation for the average car, and we can compare to electric cars, ridesharing systems, transit, and other active modes, for fixed and variable costs, external and the user time and risk. We can see that in most private cars the user time cost is very high, as well as externalities and the cost of the vehicle. The price represented is similar between most of them, shifting a little bit the weights. It can also be observed that in the ridesharing passenger only the user time cost in considered, giving the lowest cost; however, other costs should be added to the vehicle, even if they are not directly related to the passenger itself. For transit modes, as expected, the external market cost is higher and the vehicle cost is lower, and for the active modes such as walking, the highest cost is the time needed to use them.

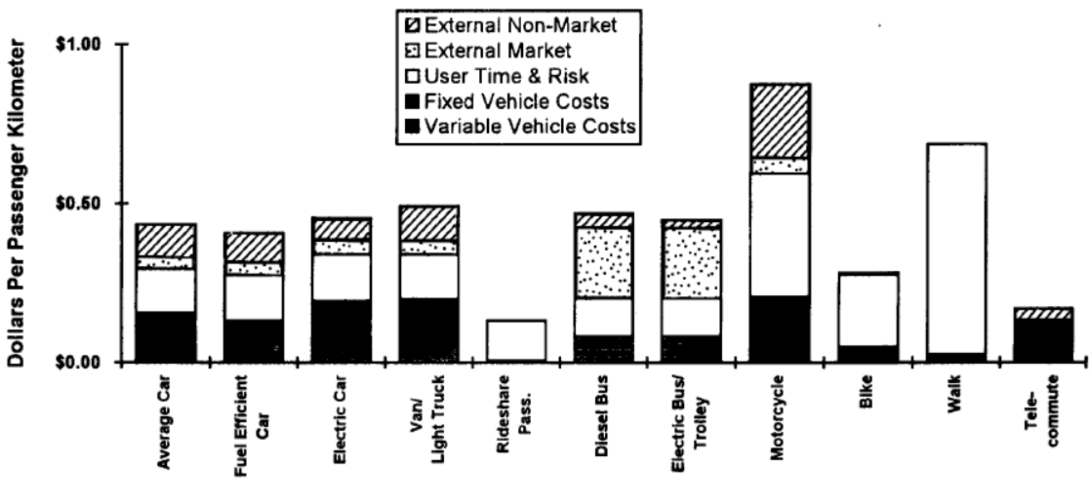

Figure 5. Average cost distribution for 11 modes of transportation by category (1996 Canadian $ ≈ $1.15 US $ today) (Litman, 1997)

If we consider in the same model only the costs of the automobile, we can see in the following figure how it is more or less evenly distributed between external costs, where nonmarket ones are higher; costs of the vehicle, where the price of it is higher than what it costs using it (variable costs); and internal costs, which are the user time and the risk.

With the implementation of autonomous vehicles, these costs would be shifted by reducing even more the variable costs and the cost of the user time; and external costs would still have a higher impact that should be considered. If we consider the idea of a ridesharing system of AVs, the analysis of the cost of the vehicles would be more important to present an according pricing scheme, because the user time would be important but also how the other costs are internalized with the price.

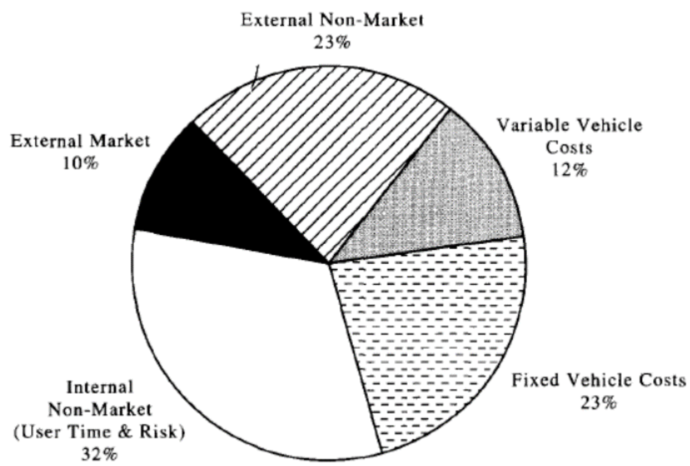

Figure 6. Distribution of automobile costs by type of cost (Litman, 1997)

Using a general classification between the most important cost types such as variable, fixed, internal and external, we can find from the Victoria Transport Policy Institute (Litman, 2009) a classification with some of the most important costs (Figure 7).

This study analyzes the costs of the same eleven modes considered in Litman 1997, with more detail in some respects. Then it focuses more on average automobile costs considering analysis of compact car, electric car and rideshare passenger.

The study indicates that on average about a third of automobile costs are external and about a quarter are internal but fixed. Fuel efficient and alternative fuel vehicles tend to have somewhat lower external costs. Transit tends to have lower total costs under urban-peak conditions. Ridesharing tends to have the lowest marginal costs. Motorcycles tend to have relatively high costs due to their high crash risk. Nonmotorized modes (walking and cycling) have minimal external costs.

	Variable	Fixed
Internal (User)	Fuel Short term parking Vehicle maintenance (part) User time & stress User crash risk	Vehicle purchase Vehicle registration Insurance payments Long-term parking facilities
External	Road maintenance Traffic services Insurance disbursements Congestion delays Environmental impacts	Road construction Subsidized parking Traffic planning Street lighting Land use impacts

Figure 7. Classification of transportation costs (Litman, 2009)

We can see in the figure 8 the estimated costs of urban driving of an average car. The values are obtained from Litman ,1997, and are very similar to the ones presented in the study of Litman, 2009, which is used for a new microcomputer software program, Transportation Cost Analyzer, and can help incorporate full costs into planning and policy making. As we can observe travel time has the higher cost, followed by the cost of the car (first the fixed cost of purchasing it and then the variable costs of operating). This is very similar to the average models presented in the previous chapter, where the travel time and the time lost because of congestion were the most important variables considered to account for their costs. The rest of the variables are important but have a lower value than the previous ones (values are 1996 $US which are approximately equivalent to $1.64 due to inflation).

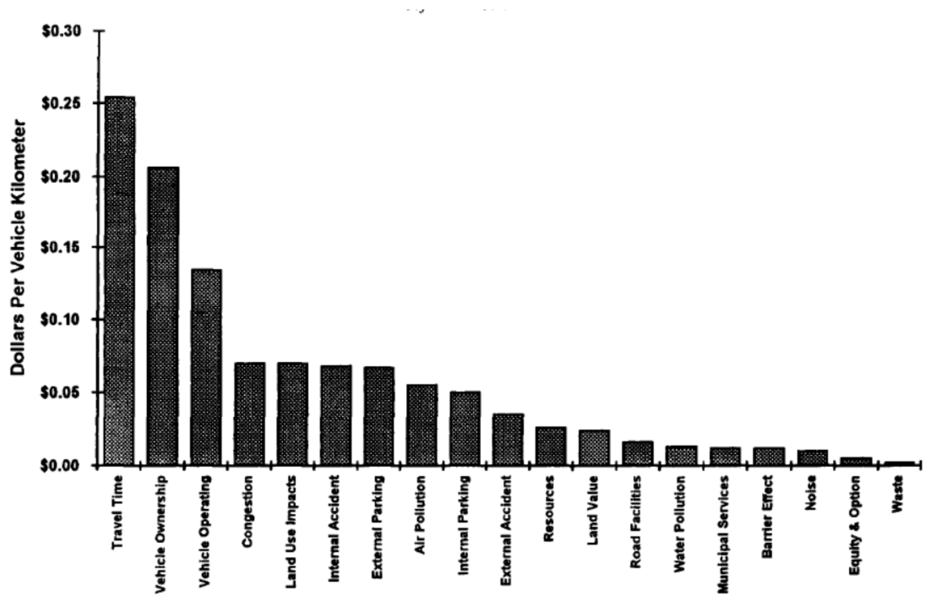

Figure 8. Estimated average costs of urban cars (Litman, 1996)

The second example mentioned appears in Small, 2007 (Figure 9). This study is focused more on average variable costs of urban automobile travel by using empirical data. Even if it does not include the other modes for comparison, the study is very useful as the data can be related to the costs of private autonomous vehicles, which is the focus of this research. It is focused on US urban commuters and presents estimates in US dollars per vehicle-mile, at 2005 prices, for a medium-size car. Given this situation, the study makes some assumptions such as not including parking search costs and the trip distance and time being for the average US urban commute using private modes, namely 12.1 miles and 22.5 minutes (implying average speed of 32.3 mph). These are estimates from the 2001 National Household Travel Survey (Hu and Reuscher, 2004). If we consider recent values, it is a bit higher: 25.7 minutes (Bureau of Transportation Statistics, 2019).

The above study distinguishes between two types of variable costs: private, which includes fuel taxes and use's own congestion costs; and social average, which excludes taxes but adds external costs; and also separates between average for the total cost divided by total vehicle-miles, and the marginal social costs for the incremental cost due to one additional vehicle-mile travelled.

Type of cost	*Private*	*Social*	
	Average[a]	*Average*	*Marginal*
Variable costs			
Costs borne mainly by highway users in aggregate			
(1) Operating and maintenance	0.141	0.141	0.141
(2) Vehicle capital	0.170	0.170	0.170
(3) Travel time	0.303	0.303	0.388
(4) Schedule delay and unreliability	0.093	0.093	0.172
Costs borne substantially by non-users			
(5) Accidents	0.117	0.140	0.178
(6) Government services	0.005	0.019	0.019
(7) Environmental externalities	0	0.016	0.016
Short-run variable costs	0.829	0.882	1.084
Fixed costs			
(8) Roadway	0.016	0.056	
(9) Parking	0.007	0.281	
Short-run fixed costs	0.023	0.337	
Total costs	0.852	1.219	1.084

Figure 9. Costs of automobile travel for US commuters in US$ per vehicle-mile in 2005 price (Small, 2007)

And some of the most important variables are the operating and maintenance, vehicle capital, travel time and environmental externalities. In our research we will use this type of analysis to consider the most important variables in our situation and some values to use as reference or how we should adapt them depending on the scenario.

CHAPTER 2:
Analysis of the Distribution of Vehicle Usage and Trip Information

Introduction

The aim of this chapter is to present the analysis of the distribution of vehicles depending on their type, age, and use, and on the purpose and characteristics of the trips in the US. The information presented is useful for the present and future studies involving new mobility systems which may substantially affect the usage patterns of vehicles and thus the associated costs. The objective is in eliciting information of use in modeling transportation systems of the future.

The personal vehicle is the most common mode of mobility for people, but its average usage is very low, with an efficiency lower than 4% of its total seat-time, as explained earlier in the background section. The implementation of shared mobility services, in particular on a subscription basis for better control and implementation, can drastically increase this efficiency by reducing the number of vehicles needed for the same level and quality of transportation. However, this would increase the usage of the vehicles by an equivalent amount in time and miles. Under this scenario, it is crucial to analyze these effects, and how agents interact among them as subscription services are implemented. Any detailed analysis of such systems will need to be at the individual level and thus modeling efforts are expected to be with agent-based simulations, which require more insightful information of the trips and the modes currently used. Information of particular significance are the distributions that need to form the input for any modeling exercise.

It is of highest importance to observe which type of vehicles are most owned and used, how these different vehicles serve a purpose in the daily trips, their life-span with that usage level, and how the different types of trips can affect the usage of different vehicles. For that purpose, we make use of the dataset from the National Household Travel Survey (NHTS, 2017). We analyze the information, which consists of travel behavior data on trips made by all modes of travel for all purposes.

In the following sections, we first analyze the information regarding the vehicles, their type, age, mileage, and distributions, and we follow with an analysis of the trips and its purpose types, along with their relationship to the different vehicle types. We then provide a section with the analysis of the vehicles purchased per year, and a study to estimate the vehicles being destroyed. We finish the chapter with conclusions that are useful in present and future modeling impacts of ridesharing systems, and correctly analyzing the changes and interactions of agents in the transportation system, which would be presented in following chapters of this dissertation.

Description of the Survey Data

The National Household Travel Survey is the source of the nation's information about travel behavior by US residents in all 50 States and the District of Columbia. It includes trips made by all modes of travel (private vehicle, public transportation, pedestrian, and cycling) for all purposes (travel to work, school, recreation, and personal/family trips).

The NHTS data is collected directly from a stratified random sample of U. S. households. It provides data on individual and household travel behavior trends linked to economic, demographic, and geographic factors that influence travel decisions, and thus it is of use in forecasting travel demand. NHTS contains information from more than 130,000 households and includes the information of all trips taken within a 24-hour period by all household members aged 5 or older; and illustrates (Figure 10) the relationships between the household, person, travel, and vehicle data and includes examples of the core variables collected.

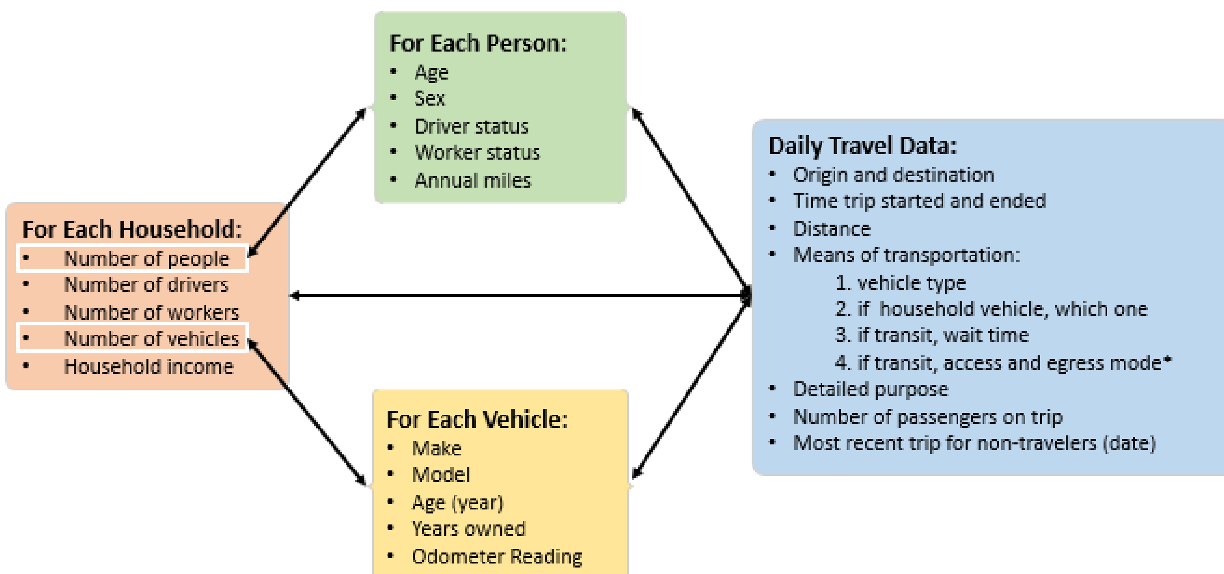

Figure 10. Survey information and relationship between variables (NHTS, 2017)

Vehicle Distribution Analysis

In this section we provide an analysis of the distribution of vehicles and their characteristics. The objective is to generate a reliable distribution of the different vehicle types and to analyze their characteristics to see their possible impact in the shared mobility simulations.

The main issues we encounter in this type of data analysis are the number of entries of the survey and the amount of information to analyze. We make use of Python and included packages to analyze the dataset. There are several data treatment issues of concern. For instance, there are some entries in the NHTS data set with incorrect responses, format or implausible numbers assigned to them. As an example, we cannot consider vehicles with negative values in their age, or with impossible total mileages.

The following analyses are on the basis of data that is pre-processed and cleaned. This process consisted in reviewing the information included in the databases and fixing and removing incorrect data entries. We paid specific attention to incorrect formatting as well as duplicated and mislabeled information. Some examples of this type of incorrect information were vehicles with negative values in mileage or year, wrongly assigned vehicle types, or impossible numbers of trips or households. The problem with this type of entries is that it can generate incorrect outcomes or outliers in the representations. For this reason, such entries were removed before being analyzed and processed; however, this only represented a small number of entries in the database.

Vehicle type distribution

Initially, the most important aspect in our research is to consider the distribution of vehicle types that represent the population of the United States in trips. In this analysis, we compare the information obtained from the vehicle and trip dataset. Not only do we want to consider the types of vehicles owned, but also how these different types of vehicles are used in terms of the number of trips and total miles used (Figure 11).

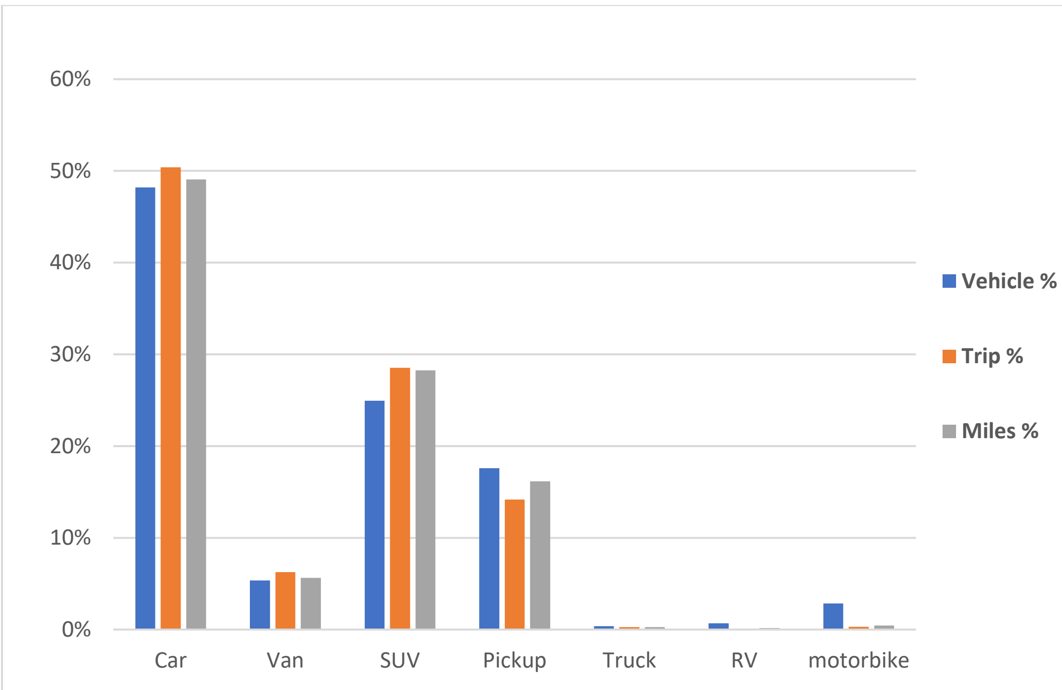

Figure 11. Vehicle type distribution (function of vehicles owned, trips or miles travelled)

As we can observe, the car is largely the most owned and used mode, with almost 50% in every case. The type of car associated with it is a regular five-seater sedan. It is followed by the Sport Utility Vehicle (SUV) with about a quarter of the total, and then other types such as pickups and vans. Finally, we have some information about other personal vehicles such as trucks, RVs, and motorbikes, with values lower than 3%. This information closely follows the idea that the regular car is the most owned type of vehicle, and that it is also the most common mode used in daily trips, with other types of vehicles used less in some situations.

If we compare datasets, we can observe that the results are similar. There is a high correlation between the distribution of vehicle types owned and used, with small changes in the non-predominant modes. As such we can observe how the percentage of SUVs increases in the trip dataset, with the reduction of vans and pickups in a similar way. We could infer that in some scenarios people are more willing to use their SUV for their daily trips, but not as much as their vans or pickups, which could be reserved for trips of particular purposes. Most of the people who buy an SUV as their personal vehicle use it, whereas vans and pickups are not used as much.

However, the percentage of use of pickups, RVs, trucks, and motorbikes increases a little when we consider the total miles used on the trips. This could indicate that those types of personal vehicles are used in less trips but for longer distances, whereas cars, for example, might be used for many trips, even if they are very short. We will further analyze the differences between types and the purpose of the trips in following sections, where we consider more in depth those elements from the dataset.

We compare the results from the NHTS2017 survey with the ones obtained in the sample of households that constituted the 1995 National Personal Transportation Survey (NPTS). NPTS consists of over 42,000 households contacted between May 1995 and July 1996. The NPTS households reported on over 75,200 vehicles across more than 200 makes and models, and the survey information was used in several studies, in particular in the paper presented by Zhao in 2002. There, the car, or passenger car, was the predominant mode with an even higher share of about two thirds of the total number of vehicles considered. Then we would find the rest of the types with the pickup around 17%, and the SUV and minivan with similar shares of 7.4%.

We can observe how in the NHTS survey, more vehicle types are considered and there is more dispersion in the distribution of vehicles. We could infer, at least from the 1995 data, that people choose to have more types of vehicles, even if they still prefer to make use of the regular car. In addition, companies have increased their production of other types of vehicles, and the number of vehicles per household has also increased. In particular, we can observe the increase in the share of SUVs, making them a bit more predominant in the current number of vehicles and type chosen to make regular trips.

The information obtained can also be compared with a study presented by Choo and Mokhtarian in 2004, from a survey with data from San Francisco in 1998. They focused their analysis on the importance of choosing the vehicle type depending on the characteristics of the trip and the owner, such as the distance of the trips, or the income or age for the owners. They analyzed more vehicle types, making more classes for the one considered as a regular car, and concluded with the different characteristics associated with each different type, for example, using compact cars for people who work, which makes it very present in the middle class and single adult households.

What interests us more is the distribution of vehicle types that they presented. We can see similar results as in Zhao in 2002, and close to the results presented here from the NHTS, 2017. The regular car would have a percentage of about 50%, and it would increase as we consider large, luxury and sports vehicles (which are not distinguished in the other studies). Then we would have SUVs with a 10% share with the remaining shares being pickup and vans. This information helps us understand the distribution of vehicle types, and how it has changed over the years. It also gives us more information that would be useful to better simulate new shared mobility systems, and how by considering different vehicle types and the cost associated with each one of them. We can analyze the interactions between the agents in the system and improve the transportation system by reducing the number of vehicles needed and the total cost of using the vehicles, while keeping a similar level of service.

Vehicle age and mileage distribution

Now that we know the distribution of vehicles, we are interested in analyzing how many of them are new, and how this can affect a shared mobility study. Our approach is to link the odometer information with the corresponding age of the vehicles. One of the key aspects of the shared mobility simulation is the increased mileage compared with the non-shared scenario. This would imply that vehicles are more used in a lower amount of time. In the current situation, regular cars have an associated life cycle of 10 to 15 years with a use of about 15,000 miles per year. With shared mobility, we can expect to reduce the number of vehicles, increase their annual mileage, but at the same time, reduce their life-span. For this reason, we want to analyze the current situation in terms of age, odometer, and annual mileage.

As we can see in the number of vehicles for each vehicle group (Figure 12), the majority of the vehicles are in the range of 0 to 10-15 years. This follows the idea of a vehicle life-cycle of around 15 years. We can observe how the majority of vehicles are newer and then slowly the number of vehicles for following years starts decreasing. As time passes, vehicles get old and as such, they get disposed. Only the vehicles in a better condition are able to last longer than those 15 years, even for more than 25 or 30 years. However, those vehicles are associated with a lower use and the correlation between the age and their mileage will be further analyzed.

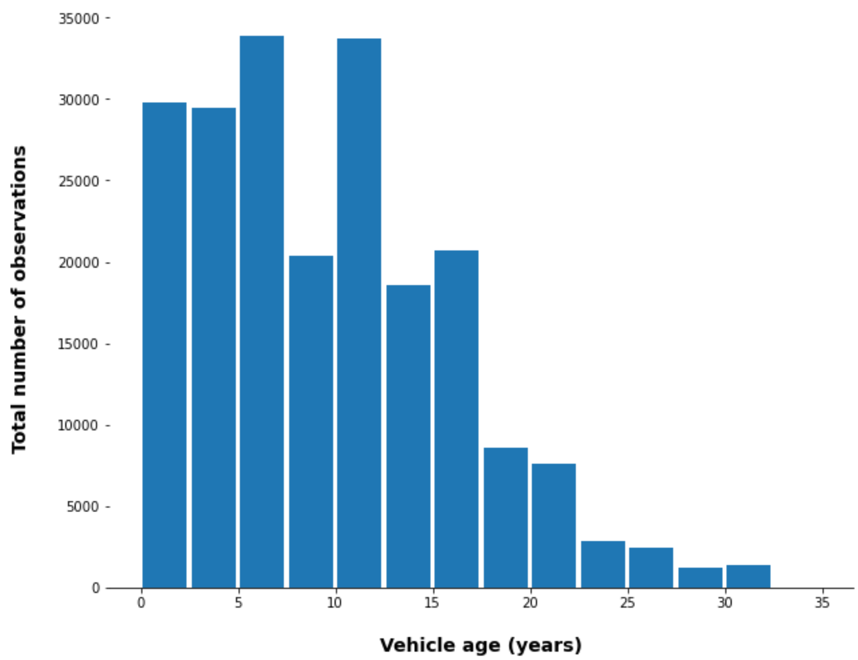

Figure 12. Distribution of vehicles depending on their age

There is only a small step back in this distribution, which corresponds to the vehicles in the 7.5-10 years of use. Those vehicles could have been less represented in the survey, extremely used and thus broken, or simply have a defect during their fabrication. However, as we will consider in the analysis of the new vehicles purchased per year and their removal, we will observe how around 2008, 2009 and 2010, the number of new vehicles purchased was much lower, probably following the economic crisis at the time.

If we similarly analyze the vehicles now using the odometer information, we can observe, a more clearly decreasing pattern in the use of vehicles (Figure 13). Not only we can observe how as vehicles age their number decrease, but in particular, as we could think, the more that we use them the less vehicles that we find. But more importantly, we can get better information at how much vehicles are used before we get rid of them, and a better number in the total life cycle of vehicles. This could be situated around 250,000 and 300,000; and assuming of 15,000 miles per year, should give us a life of 15 to 20 years.

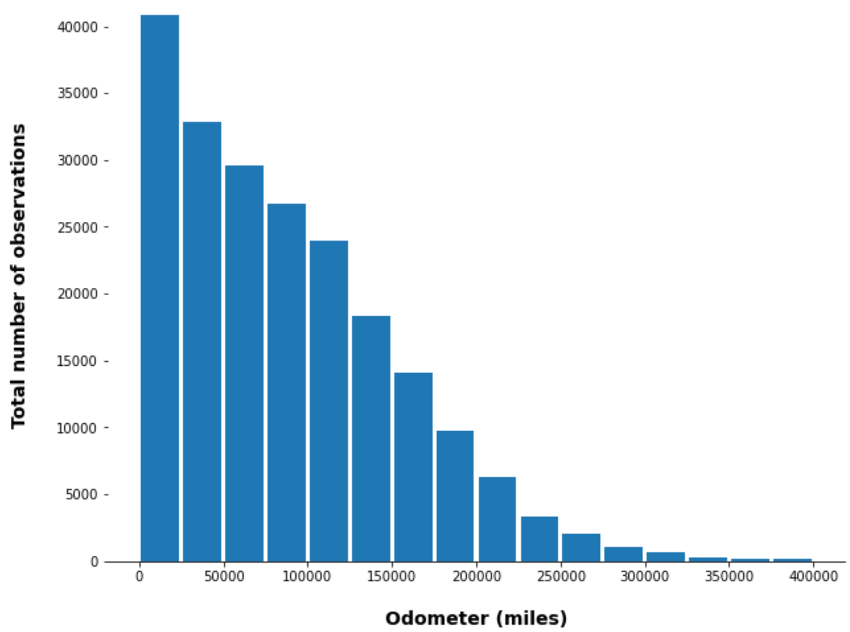

Figure 13. Distribution of vehicles depending on their odometer

We could then conclude that the vehicle mileage gives us a better approach at analyzing the life of a vehicle and its cycle, a little bit contrary with what is done in studies that usually focus in how old they are. This gets extremely important in shared mobility studies, where mileage gets more importance as vehicle are used more, and their life cycle span would be considerably reduced.

The next step is to consider the relationship between both variables: how much a vehicle is used (average odometer mileage) and its age. The results show a curve around the 20/25 years mark, contrary with the monotonically increasing line that we could expect (Figure 14). For the initial few years, a linear relationship can be seen, indicating a fairly constant usage per year. However, the relationship turns into a curve with even a decrease after the 25 years mark. The decrease is certainly occurring due to averaging.

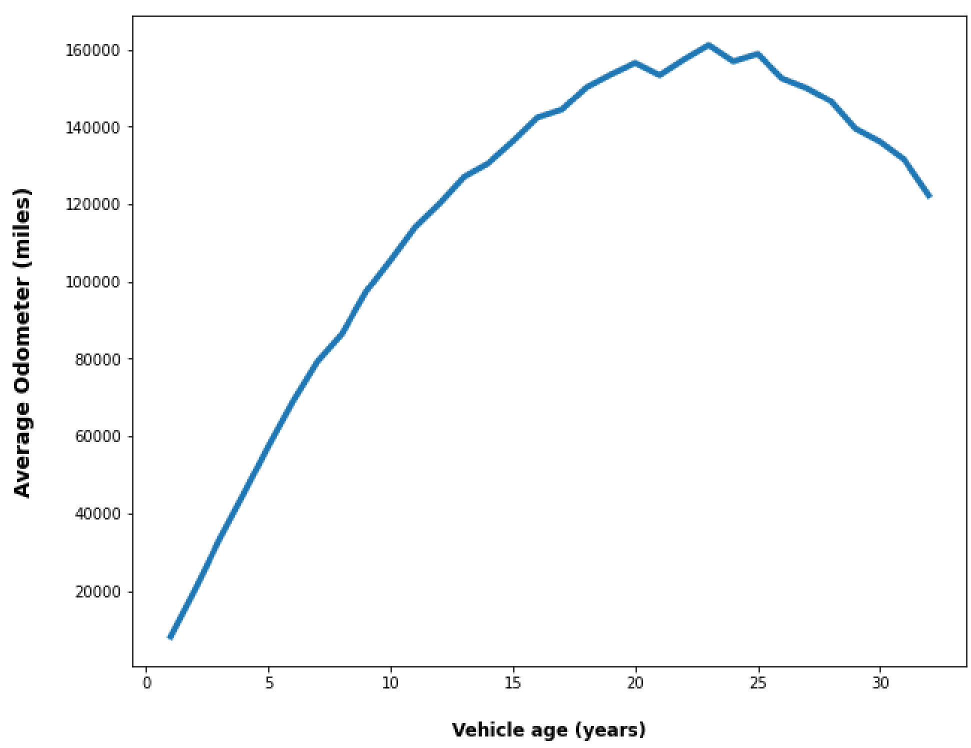

Figure 14. Relationship between the age of vehicles and their average total mileage

As vehicles leave the population due to age, the number of vehicles starts getting very low, reducing the volume of the dataset but also with vehicles that are used very little every year and some not even usable anymore. From that, we can infer that in general vehicles are used at a similar average rate during the first 10 to 15 years, and then they start to disappear. The main reason is naturally that the costs to repair, maintain or replace them are too expensive. As a result, in the highest age values, we only find the vehicles that are able to survive, which ideally are the ones less used and that have had a better control and maintenance. This category might also include antique vehicles and collector models, which can be a pastime for many car enthusiasts.

With that information in mind, we found it very important to contrast those results with the broad consideration used in transportation analysis and simulation that vehicles accumulate in average a mileage of 15,000 miles per year (Figure 15). We can observe how (orange line), in the first years, vehicles follow a similar estimation to the ones represented in Figure 14 (blue line). However, the relationship slowly drifts apart after the 10/15 years, being very distant for the oldest vehicles considered in the survey.

This would be very important for our considerations in the agent-based simulation: as shared mobility would increase the use of vehicles, the mileage, the costs associated to their use, and reduce the life cycle. In particular, when and how vehicles should be replaced, would have more importance than it has been given in previous research. Furthermore, this information helps to understand the importance of considering the mileage associated with vehicles instead of their age. This would be especially important in the consideration of the cost of the vehicles, and how, with the proper framework, we might be able to improve the improve the implementation of ridesharing systems.

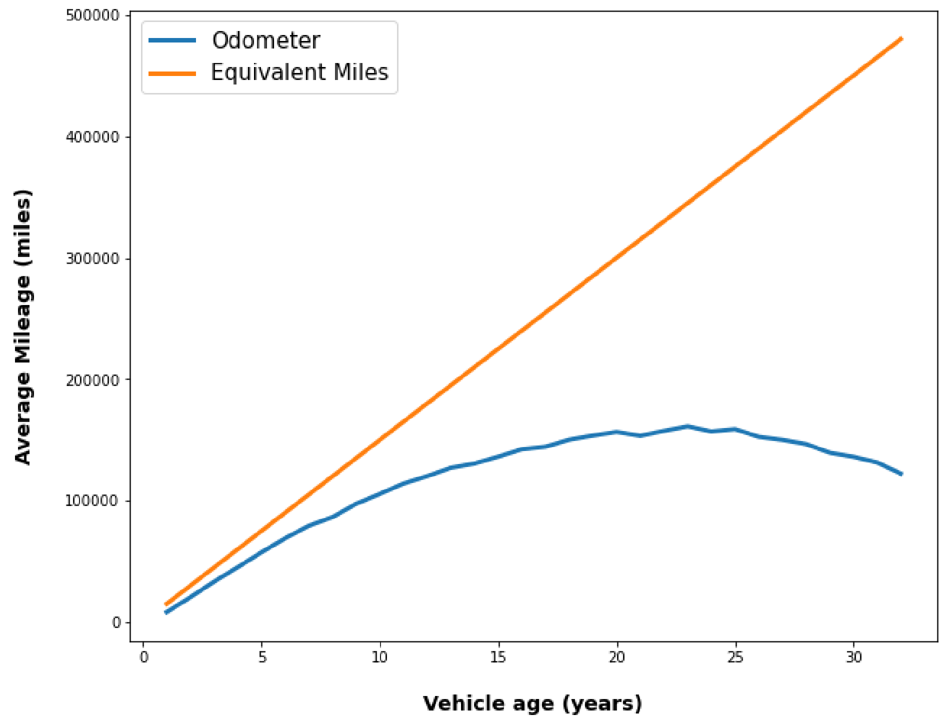

Figure 15. Comparison of the relationship between the age of a vehicle with the associated mileage (blue line) and with the estimated mileage (orange line)

Trip Distribution Analysis

Once we have analyzed the information about the vehicles' type and use, we focus our attention on describing and understanding the trip information, to analyze their distributions and be able to show the findings which should be included in our simulation. We have already considered the impact of the vehicle type distribution, along with the vehicle dataset. Thus, our first step would be to analyze the different trips depending on the vehicle, the purpose, and the duration.

Distribution of trips depending on vehicle type

We have presented the distribution of vehicle types depending on the vehicles owned. However, it is important to understand how these vehicles are used and to observe the effect of owning those vehicles compared with their daily use. For this reason, we analyze the average daily and total miles used of vehicles, and the total number of trips done per day depending on the vehicle type.

The car is again the most common type used, for the majority of the trips done and miles travelled. However, the trips made are not very long, and they average to lower trip lengths. On the other hand, other types such as Van or RV accumulate a very low number of trips and miles, but they are used to travel longer distances. Finally, we find some other types in a middle situation, with the SUV or the pickup accumulating some trips and miles but not averaging a high mileage per trip (Figure 16). We can infer from this results that drivers tend to use different types of vehicles depending on the characteristics of the trips, and one of the most important variables considered is the distance of them.

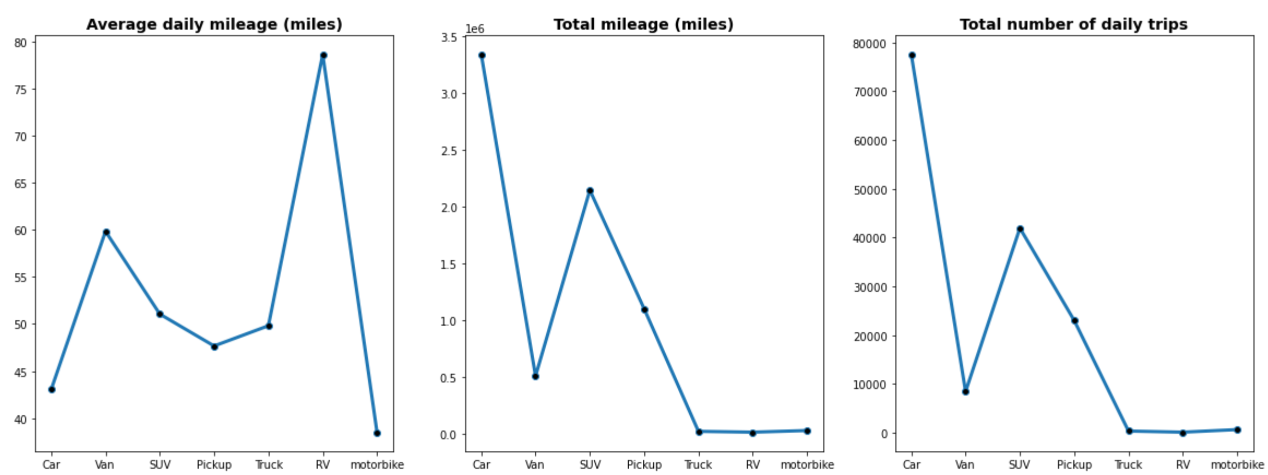

Figure 16. Distribution of vehicle types with the average daily mileage, total miles, and total number of trips

Distribution of trips depending on trip purpose

To analyze the mobility of people and be able to replicate transportation patterns it is important to consider the characteristics of the vehicles and the relationship between vehicle types and trips. Trip purpose is one of the most important characteristics, as transportation is by definition considered as a service product. This means that usually what really matters is the activity taking place at the destination, which defines the purpose of the trip and is associated to the destination. Thus, depending on their purpose, people might consider using different vehicle types.

We distinguish nine different types of trips depending on that purpose: Home, Work, School, Medical, Shopping, Social, Driving (somebody else), Meal (going to eat), and other miscellaneous purposes; and for each one we consider the distribution of the trips depending on the average daily miles, total number of daily miles, and the total number of trips (Figure 17). The average miles per trip varies depending on the destination purpose between 6.5 and 12.5 miles per trip.

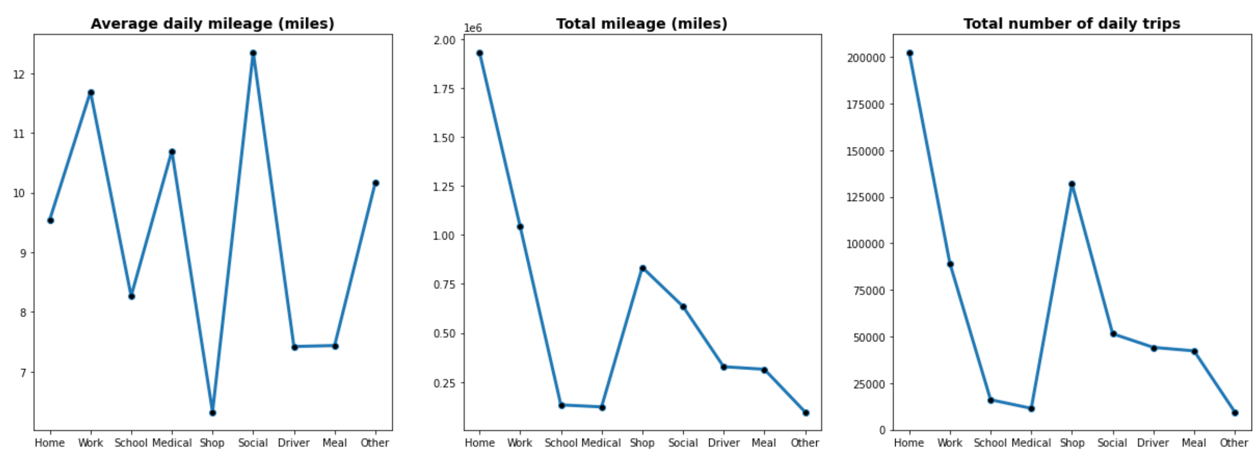

Figure 17. Distribution of trip purposes and the average daily mileage, total miles, and total number of trips

These results allow us to infer the willingness of people to do certain trips depending on their purpose. They are willing to travel further distances to go to work, to the doctor or to meet with friends or family, however, they are not as willing to travel that far to go to school, shopping, eating or if they need to drive with someone. This might suggest that people look for areas with their choosing of schools and shopping, and this might conditionate as well the time they would like spending on driving friends. However, they will be willing to live at a place they like more even if its further from their work, doctors or friends and family; but even so, they are still willing to drive to those places. This might be associated as well to a change in people's perception on accepting driving longer distances to work and to the doctor, but not to school for example.

We can also obtain more information in terms of the total use of vehicles for those purposes, either in terms of trips or in terms of mileage, where we observe a similar distribution. The highest number of trips are to go home, which seems to imitate reality as most of the trips on a daily basis are round trips with the origin at home, and then coming back after their purpose is served. That, combined with their value of average miles per trips, gives us the highest total mileage as well. For the rest of the trips, we can observe how most of them are to go to shopping or to work, and then we would have the rest.

Finally, we could consider the proportion of home trips compared with the other. In a scenario were we only had trips from and to home, the total number of home trips should be the same as the summatory of the trips of the other types. However, when we compare the numbers, we obtain that about 34% of the trips have home as their destination.

We could infer from this information that a little bit more than half of the trips return home, whereas the rest could be considered as chain trips that have more than one purpose before coming home, or that don´t return that day.

One of the key aspects in modeling real-world contexts is to input data for the kind of capabilities provided by agent-based platforms that can consider a destination location for the trips, with a certain activity associated to any such location. This means that we would be able to better tailor the purpose of the trips, and its distribution, considering the information that we know about their purpose. The above analysis helps in providing the distributions to generate data for such modeling research.

Distribution of trips per purpose and vehicle type

Another consideration in our study is that the purpose of the trips can be associated with a different vehicle type. If we plot that relationship, we can observe in the how there is a parallelism between almost every vehicle type and the activity of the trip (Figure 18). There is only some overlap between pickups and vans when they are driving somebody else, which could be associated with the ease of the latter to be used for that purpose. We can infer that, in general, there is a distribution of the purpose of the trips, but the vehicle type associated does not have much effect. People use the personal vehicle that they have for almost any purpose trip, with the car being the most common mode, followed by the SUV, the pickup and the other vehicle types considered.

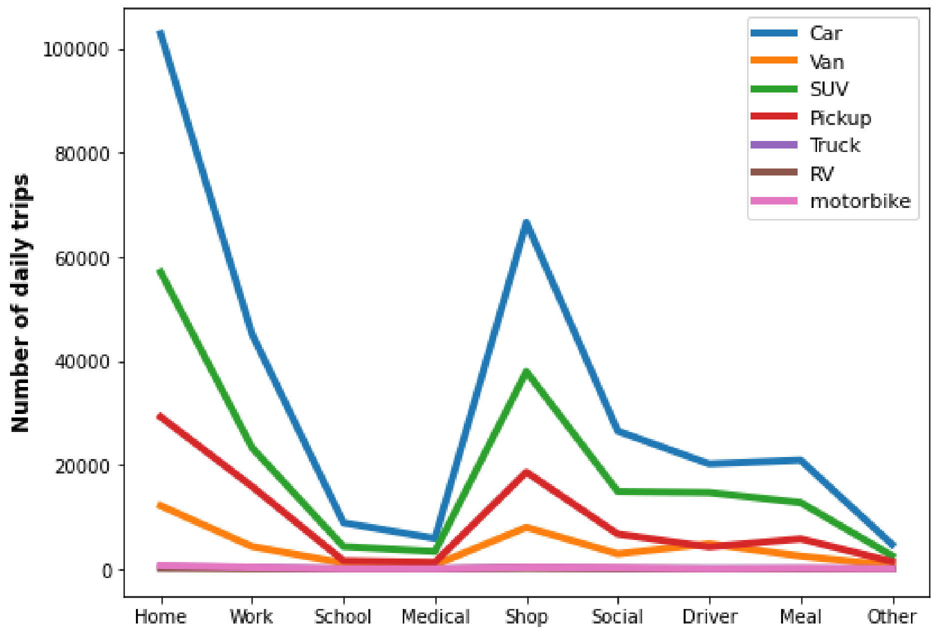

Figure 18. Distributions of relationships between trip purposes and vehicle types

Distribution of trips depending on age of vehicle

Following the previous section of the relationship between the mileage associated with vehicles and their age, we wanted to make some considerations including the information from the trips. If we group the trips using the age of the vehicle used, we can obtain how much they are used in total and in average.

In

Figure 19, we can observe how younger vehicles are used more, and that there is a decreasing pattern as they get older. There is a dip at around 7.5 years, which is caused by the lower number of vehicles from that year. Not only older vehicles are used less, but also their average daily miles are lower, with even some erratic numbers for the last age groups given the scarcity of survey information, but still a decreasing tendency towards their age and miles. These findings reinforce our hypothesis in terms of vehicle use, and also the idea that only the vehicles that are used less survive. So, in modeling any shared mobility system, the age of the vehicles, and more importantly its use and mileage, would have a crucial role.

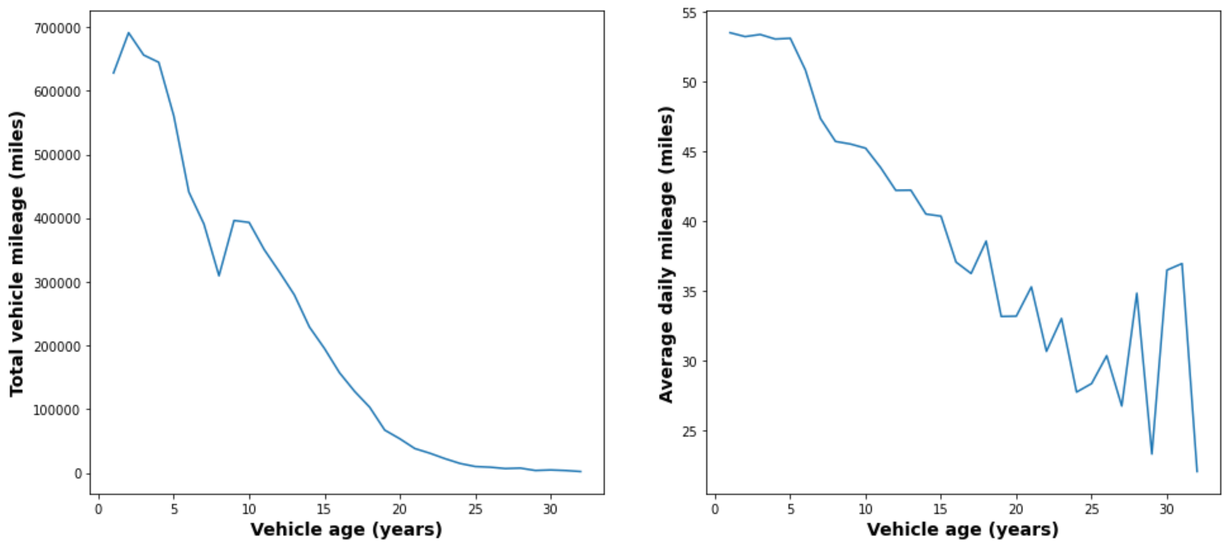

Figure 19. Distribution of the age of vehicles and the aggregated daily miles, and the average daily miles

Distribution of Destroyed Vehicles

The key aspects that we think are crucial for the modeling of shared mobility systems is the consideration of how vehicles are used, the impact of any increased miles from mobility-sharing and the determination of when a vehicle should be disposed of. Given the results obtained during this analysis, we see the importance of considering the total mileage of a vehicle, and not only focusing on its age. For that reason, in this section we present an estimation of the percentage of vehicles being disposed from the total number of vehicles being purchased in the US. This will give us an idea of the distribution of vehicles disappearing, and how could we make a transformation of this information and their age, to present a relationship for vehicles dying in terms of their total mileage.

In the first step, we analyze the total number of cars being sold in the US from 1950 to 2019 (BEA, 2021). There is some variation from year to year, however, we can observe certain increase in the number of cars being sold up from 1950 to 1975-1985 (Figure 20). It could be the result of a strong set of policies and government decisions facilitating the use of the personal vehicle in a day-to-day basis, and the variations, the product of different economic situations, usage patterns or vehicle policies, not considered in the scope of this report. Then, it slowly starts decreasing until 2019 with only a big variation around 2008, which as commented could be the result of the big economic crisis around that year.

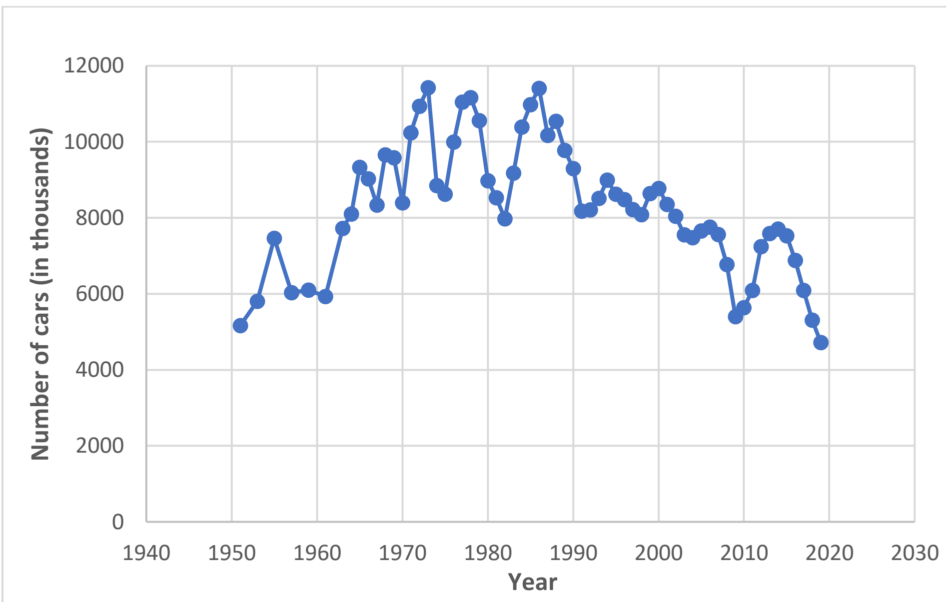

Figure 20. Distribution of vehicles sold in the US 1951 to 2019

If we make use of the above information, we can obtain the number of vehicles being sold each year, and thus, the number of new vehicles. Similarly, we can use the vehicle database from NHTS 2017 to obtain how many vehicles remain from each year, by considering their age. Then, we can extrapolate the initial information by assuming that the vehicles with less than one year correspond to the total number of vehicles being sold and that no vehicle had already been disposed. We can estimate the percentage of vehicles that have been removed from the total number of new vehicles each year and the ones remaining. Finally, we can use the estimation of 15,000 miles used per year per vehicle to estimate the distribution depending on the mileage of the vehicles.

We can observe from the results that on average the number of vehicles “dying”, as expected, increases as the vehicles are more used (Figure 21). We can notice how there is a change in the rate of vehicles being disposed: initially we could observe a lower slope, which after 200,000 miles gets bigger and rapidly increments the percentage of vehicles being disposed. After the 225,000 miles there remains less than half of the vehicles sold that year, and right after the 300-350,000 miles, the slope decreases again.

The percentage of vehicles remaining at that point is less than 10% and only a few remain, the ones which have had a better maintenance, lower use, or better conditions overall. Such information would be particularly important in new shared mobility scenarios, as the effect of mileage would be more important, and the ratio of vehicles being disposed would impact the cost of the system and the necessity of vehicles having to be replaced. However, this type of findings would be more accurate with more accident analysis information, using which we could correspond the disposed vehicles and their mileage with the proportion of vehicles involved in accidents after which the vehicle could not be fixed, or it would be too expensive.

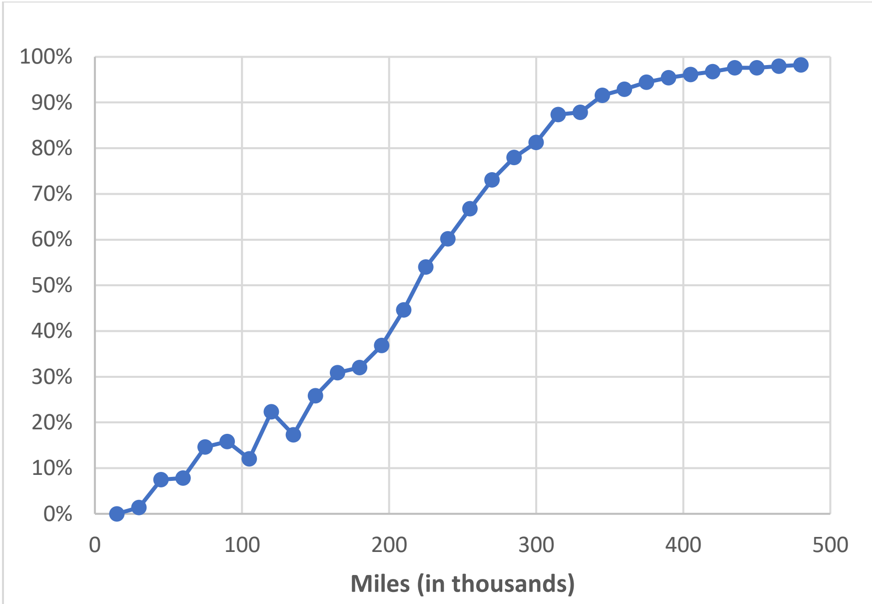

Figure 21. Distribution of estimated removed vehicles in percentage from the total number for the equivalent mileage

Potential Impact of the Current Situation

The information presented in this chapter is based on the survey from the NHTS in 2017. We would find that the conclusions obtained from this analysis would be significant and would benefit current and future transportation simulations, especially the ones including new mobility systems. However, we would like to add some considerations that would include changes in the mobility since the date oof the survey. In particular there have been some changes regarding the incorporation of electric and autonomous vehicles, and also the impact of the virus COVID-19 in our society. There are currently some studies that try to analyze in detail the impact of such events, which is not the purpose of this dissertation, however, we would like to add some comments and considerations regarding those matters.

Electric vehicles seem to be gaining more importance in our society. They might still be a small percentage of the total number of vehicles, and as such might still not be very significant in the vehicle type distribution if we considered them as a different class. However, they are increasingly being incorporated into our lives. They are being developed for use in almost every type of mobility systems, with more importance given to the personal vehicle sector. As such, we would not expect a change in the distribution of vehicle types, and the ones presented here would still be representative. We might only expect the regular car to have even more importance.

Autonomous vehicles are deeply related to the electrification of cars; however, they are still in an early stage of implementation. They might not be very representative, but we would expect that they would have more impact in the future. In a similar way, we would expect a comparable impact with the electric vehicles, with similar shapes for the vehicle distributions.

In terms of vehicle age and usage, we would expect a similar shape in the mileage-age curve with the implementation of electrification and autonomy. We would also consider an increased usage and longer life lengths, as electric vehicles might be considered to have fewer mechanical issues and less maintenance costs, in particular, due to the lack of combustion engine. In a similar way, these considerations would affect the related curves, reducing initially the number of vehicles being disposed and shifting to the right the curve of vehicles destroyed with respect to their mileage. Although, their impact might not be very direct initially, we would think that an increment in the number of electric and autonomous vehicles would facilitate the emergence of new shared mobility systems. This combination would shift even more the usage curves, increasing their daily and total mileage, and might even affect the trip purpose curves, generating more trips that could be considered as driver, where the purpose of the vehicle in the trip is to take the passenger to its destination.

Even before finding the possible impacts of electrification and autonomy, our society has been hit with a global pandemic (COVID-19 that spread since early 2020) that has affected people in every way imaginable and in particular in their transportation. This pandemic was very difficult to fight, however, one common suggestion throughout the world was to minimize the movement of people. What were just considerations with an intent to control the virus, would end up having effects that would seem permanent in the transportation systems. During the first year of the pandemic, the number of trips was drastically reduced almost everywhere. People started staying more and more at home, trying to reduce the interactions with others. Because of that, vehicle sales were also dramatically diminished; the most significative trips were also reduced (home to work and work to home, shopping, and social), people started thinking if they really needed all those vehicles, and new mobility opportunities improved, as in the use of ecommerce and the subsequent transporting of goods.

While we do not further investigate these implications, we can comment that the pandemic might have accelerated in some ways what shared mobility was implementing, and that there might have been permanent effects in our society. Though there may be an initial unwillingness to share rides or even vehicles, in the longer term, one important outcome might be a change in the perceptions about owning and using vehicles, the creation and conversion of jobs into work-from-home arrangements, and an increase in the number trips to transport goods (at home deliveries). We might see in future datasets a shift in the proportions of the vehicle type trips, where there are less trips to work, from work, and shopping, and a change in the ownership and usage of vehicles.

Discussion

In this chapter we have presented an in-depth analysis of a data set of vehicle and trip information from the NHTS. We have obtained very insightful results of the distribution of vehicle age, type, and use, and of the relationship between those vehicles, the trips, and their purpose. We have finalized with the study of the vehicles being disposed and the ones that still remain.

The regular car is the most common type, but other vehicle types are increasing in use in certain situations and longer trips. The age of a vehicle serves to indicate its level of use; however, we find that the mileage associated gives a better indicator of their life cycle and how much longer we could use them. Current and previous studies considering the average of 15,000 miles per year might work for short term scenarios, but better approaches should be developed to consider the rate of use and renovation of vehicles. This gets extremely important in shared mobility studies, where mileage gets more importance as vehicle are used more, and their life cycle span would be considerably reduced.

It is important to consider the necessity of better datasets to simulate more realistic transportation systems, in particular if we try to consider new mobility options. They should include more detailed information of the vehicles, their mileage, and their costs. With this type of information, we would be able to better simulate and analyze new shared mobility systems and improve the current transportation situation.

The distribution of trip purposes plays a crucial role; however, it is not as affected by the vehicle type owned by each household. As vehicles get old, they will disappear, and only the ones with lower use and better maintenance will stay in the network. We can keep considering the 10/15 year age as a mark for the life cycle of a vehicle in some current scenarios, but as we approach new mobility options, in particular vehicle sharing or other high mileage scenarios, better mileage considerations would serve us better to optimally maintain a system of vehicles.

The purpose of this study is to indicate the characteristics of the vehicles and their trips. In particular, the findings can be applied in further research on modeling shared mobility systems which may typically be at the individual level and perhaps using agent-based models. However, any simulation or transportation modeling effort can benefit from them. We will be able to consider the type of vehicle and trip distributions, as well as analyze the impact of increasing the daily mileage of the vehicles in the network and the distribution of activities in their destinations.

Current and future work will include the application of these results and the acquisition of better data sets to generate more realistic vehicle and trip distributions. The objective is to be able to clearly understand the process of the life cycle of vehicles, the effect of increasing the daily miles they are used, and how depending on which scenarios we are considering, we could simulate the rate of generation and renovation of vehicles, especially in shared mobility situations.

CHAPTER 3:
Vehicle Usage Cost Function and Total Cost Ownership Analysis

Introduction

The previous chapters described the ongoing transformations in the transportation system: automation, electrification, and shared mobility. These transformations change the way transportation is envisioned, with new possible systems and mode combinations (microtransit, autonomous vehicles (AVs), fleets of vehicles or subscription-based mobility systems); new mobility scenarios in which vehicles are shared between the users (fleets of autonomous vehicles); and even new ownership situations where the user is no longer the owner of the vehicle and only pays for the time that he uses the vehicle.

The new transformations are expected to solve some of the problems endemic to the current transportation systems. As shown in some studies such as Sheppard in 2019, the full level of current mobility in the United States could be achieved by only 12.5 million Shared Autonomous Vehicles at a much lower cost. That number could potentially be very much underestimated, but it is quite evident that significant reductions in the number of vehicles are possible with newer paradigms of usage and ownership.

Current cost and objective functions are not sufficiently sophisticated for the kind of changes that are possible in the near future and do not consider the implications of the interactions between the new transportation paradigms. In this chapter we analyze how we should consider the importance of costs in new transportation systems and how these changes could affect ownership and usage patterns. To meet this goal, we analyze the current situation, and we generate a more specific cost function for each vehicle type to consider the new challenges that appear. These functions will be used in further chapters to analyze the interaction of supply and demand in subscription systems and present situations where we can better optimize the mobility system.

In the following sections we describe the methodology of data collection and analysis, the Total Cost of Ownership, and the generation of cost functions for the most important vehicle types.

Data Collection

The objective of this research is to analyze the changes in the traveler's usage with a new cost function that also considers different ownership paradigms, and how their interaction can affect new mobility systems of shared and autonomous vehicles, which can also include systems of fleets of vehicles.

There are many algorithms for cost optimization and fleet management but none of them considers the efficiency of the system using the total cost of the vehicle during its life. Some of the reasons are that in the current situation, vehicles have a long life cycle, and the impacts of the usage in TNC companies have not totally been analyzed. However, this scenario could change with SAVs, and in this publication we present the framework that will be used to analyze the impacts and interactions for this new situation.

This research attempts to consider the increasing importance of the cost of the vehicles, and that the variance of vehicles and demand would increase in the future (different types of trips or requests that should be addressed with different types of vehicles). Given this situation, we could differentiate between a system that has an overall optimization of the system, or a more individualized situation in which there are practical subsystem optimizations where each vehicle belongs to a company or adjusts depending on the moment.

The cost function gives a more individualized view where we can set an optimization to minimize the total cost of the ridesharing system. This will be further analyzed in the next chapters about the framework and the simulation. The objective function can be split into multiple objective functions depending on the different variables, groups of people, or fleets of vehicles. The optimization minimizes the total cost by considering a function cost for each car and adding all of them to one or separated fleets. In order to obtain this formulation, the most important step of this system is the identification of the variables that would have more impact in the costs and the subscripts of the function, depending on the vehicles, users, or fleets.

The cost function generated will be used for the vehicles considered in the simulation framework. To be able to understand the information that we need to generate this cost function we analyzed the dataset from the National Household Travel Survey (NHTS) from 2017. As commented from the previous chapter, there was a lot of importance in the vehicle types considered as well as their corresponding usage or accumulated miles on the odometer.

This information is used to determine the most predominant types of vehicles owned and used, and their distribution, which would be useful to generate the network simulation.

We obtained that the regular car is the most common type with about 50% (which we will refer as a regular or compact vehicle, or a medium class sedan), followed by the Sport Urban Vehicle (SUV) with almost 30% and then the Pickup and Van with 15% and 6% respectively (Figure 22).

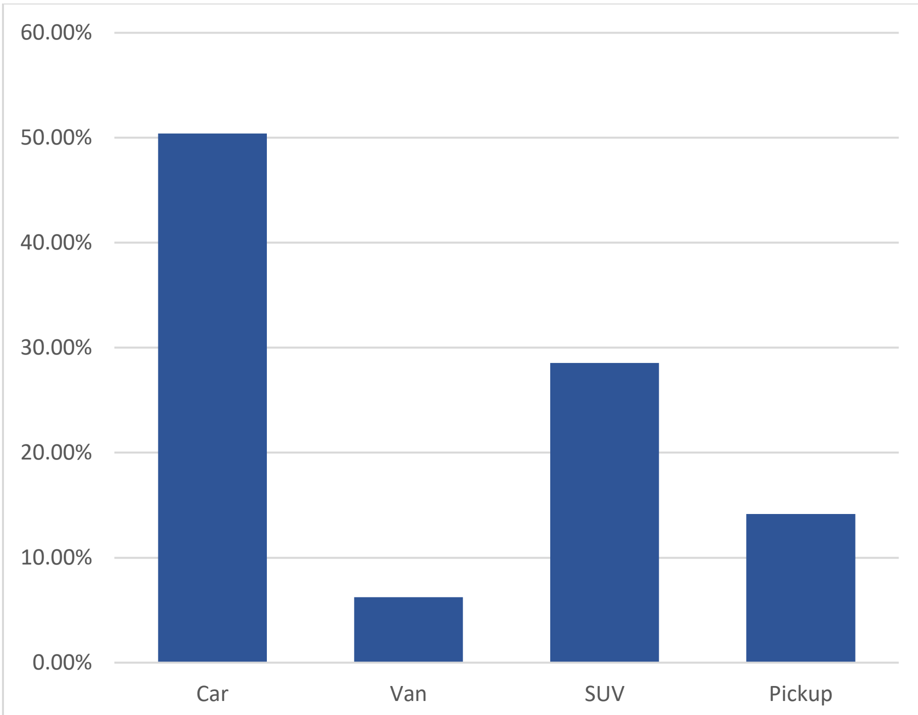

Figure 22. Vehicle type distribution (NHTS, 2017)

With those types we can generate a cost function considering their most important variables, which are the ones that affect more the total cost of the vehicle and that can change more with the increase in the vehicle's usage.

There is a crucial problem to find a clear database or information for the real cost of vehicles; in particular considering how it adjusts year by year and how it depends in the model of vehicle and region. For this purpose, we have referred to the database information from Edmunds True Cost to Own® ("The Edmunds True Cost to Own® calculator is a tool that looks at the 5-year costs of owning a vehicle, including some that vehicle owners do not consider"). From there, we can obtain yearly vehicle cost information for practically any vehicle make, model and year. The objective of this research is to present the advantages of using this type of mileage cost analysis, which in the future, would benefit from an individualized timely vehicle cost. However, due to the time and simulation constraints and without falling into the generality of the vehicle cost usage, here we select some models to represent each vehicle type.

The costs obtained from this selection would be used in our ridesharing simulation, and would be used for each individual vehicle, which would have an associated type and mileage. To determine the most significant models for each type, we have selected the four most common vehicle models purchased corresponding to the survey information from Kelley Blue Book (KBB). We selected four vehicles that had similar characteristics for each vehicle type and obtained their costs.

Initially, we wanted to obtain the information from Edmunds for the models of 2020/2021, which gave us the cost for each model for five years. However, there were some discrepancies of the costs in some models in the last and predicted future years, due probably to the lack of information or issues derived from later challenges on mobility, such as the affecting pandemic of COVID-19. Hence, we decided to get the vehicle costs information of similar models from 2016, given that we would have better information for the following five years (until 2021), and we observed how the costs were more appropriate. The only exception of this averaging was the electric vehicles. We observed how there are not many electric vehicles, and neither many different models, especially if we consider the models sold and used in 2016. For that reason, we considered the Tesla model S as a representative of the electric type and collected its costs.

In this part of the research, the values of the costs were quantified at a national level from the perspective of a rational vehicle owner, using representative values. Of particular interest here are direct, monetary costs incurred by owners and operators, such as purchasing and operating the vehicle. We did not consider other costs, such as the value of driver preferences (comfort, performance, or styling); or external costs, such as costs due to congestion, pollution, or noise impacts.

Life Cycle Costs Models

The purchase price of a vehicle is the highest cost associated with a vehicle, however, during their lifetime, there are many others that can affect their operation. In particular, if we want to compare vehicles to either purchase or make use of them, we will want to increase the number of variables that we want to consider, to choose the one that better adapts to the user necessities.

There are many studies about how to analyze the costs of the vehicles in many different ways, not only how much time they cost to their user but also how can we analyze their cost of operation. However, most of these costs are based on a life-time use of a car of 150,000 to 200,000 miles in a 10 year period. In many situations, costs models use either an average cost for the whole period considered or an average for each year from the first years of life of the car. In the new situation where SAVs would serve the same demand with a lower number of vehicles, which will mean that not only the efficiency but also the usage of these vehicles will increase, these models should not be very adequate at all. Our research considers this issue by considering a life cycle model of SAVs, which should be much lower than the 10 years of use of a current conventional car, since it is expected that in a car-sharing mode (especially in fleet systems or shared-ownership systems) each SAV may be used up to 3 or 4 times more of mileage and usage time each day.

We can find in the literature several life cycle cost (LCC) analyses of many elements, especially for other technologies like electrical applications. This type of analysis is based on the consideration of all the costs during the life of the element and as we can see in the following figure, there are many processes that have to be considered, from the acquisition to utilization and recycling (Figure 23).

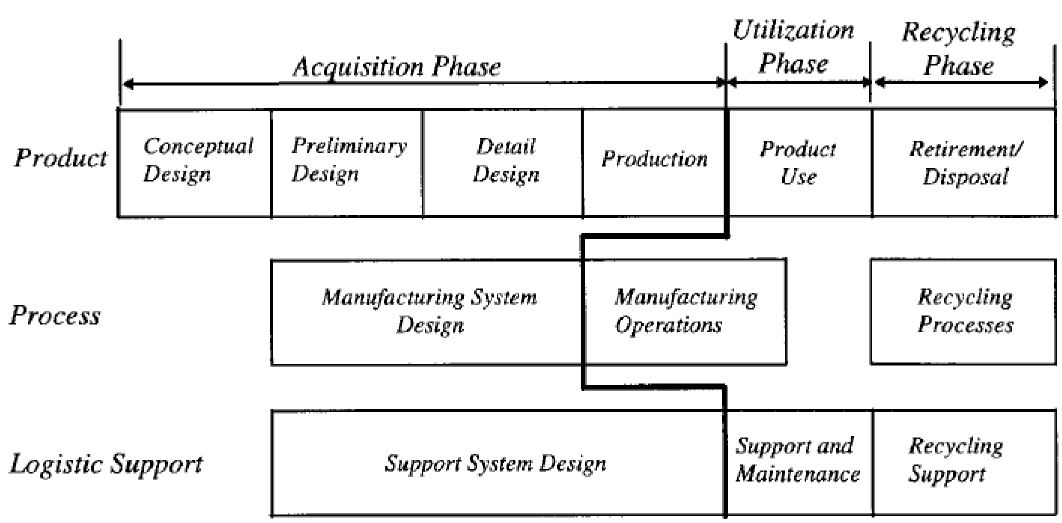

Figure 23. Life Cycle Cost scheme distribution of process and steps (Hellgren, 2007)

In the transportation literature, we also find many studies involving LCC, but they are mainly related to energy utilization or environmental impacts. We can see, for example, the calculation of the energy consumption of different types of vehicles depending on their power train in order to compare between different models and alternatives and to obtain the most efficient one (Hellgren, 2007). In addition, we can find the calculation of the environmental impact of a vehicle during its life cycle in order to observe the impact of the automotive industry in certain scenarios and to propose alternatives to that use (Liu et al., 2015).

In a framework that considers the cost during the life cycle time of a vehicle is where we find the cost information obtained from Edmunds most useful. The initial approach is to use the yearly cost information to be able to calculate the total lifetime cost of a vehicle, in what would be called the Total Cost of Ownership (TCO). This will be the basis of our vehicle usage cost function.

Total Cost Ownership

The TCO of a vehicle is the total lifetime cost of owning and operating it and consists of the purchase price plus all the related costs of operation. It is a more holistic way of looking at what a product actually costs the customer, where one not only considers the short term cost of buying it but also the long term costs from using it. As a result, the customer can obtain the true cost during the product's lifetime. In an analysis done in this manner, the vehicle with lower total cost of ownership is the one with the better value so we can use it to determine the vehicle pricing system. However, depending on how we consider these costs we would have different definitions of the TCO. In a similar manner to how it is described in the study by Burnham et al. (Argonne National Laboratory, 2021), we could distinguish between a cost from the perspective of private individuals or the society, in an approach that is totally or partially qualitative. The combinations of these options would give us the following four categories:

- Private and fully quantitative: mathematical consideration of the most important variables affecting the TCO of a vehicle for a private individual or a firm. This is the option that will be considered in this dissertation.
- Private and partially qualitative: considering the formal costs of the variables, but also partially the effect of the subjective consideration of the individual or firm.
- Society and fully quantitative: mathematical costs and benefits affecting the whole society.
- Society and partially qualitative: more informal and subjective analysis of the costs affecting the TCO of a vehicle for the society.

For the private-quantitative cost analysis we have identified the most relevant cost elements for a total cost of ownership analysis. We can combine the values of each of these cost elements in a cohesive total cost of ownership calculation and generate the vehicle usage cost function describe in the following section. In this analysis, TCO is split into nine components:

- Vehicle cost: includes the cost of purchase less the residual value of the sale of the vehicle at the end of the analysis window.

- Fuel: its cost is proportional to the driving distance, the fuel efficiency of the vehicle, and the cost of the specific fuel needed by the vehicle. The consumption assumed consists of 45% highway and 55% city driving and that the vehicle is equipped with the transmission that is standard equipment for that vehicle.
- Insurance: it covers both liability and vehicle replacement or repair, using national average of costs for light-duty drivers, and all typical costs for each MHDV vocation.
- Maintenance: includes the cost of scheduled vehicle repairs as the vehicle ages (factory-recommended items at periodic mileage), and unscheduled maintenance (Services for inspection and replacement of vehicle parts that do not have set replacement intervals such as wheel alignment and the replacement of items like the battery, brakes, headlights…)
- Repair: this cost accounts for unexpected costs to operate a vehicle after accounting for regular maintenance and fixes made while under warranty.

These are the most important variables considered in the calculation of the TCO of the most predominant vehicles in the US. These variables would have a higher impact and would also be more affected by the usage of vehicles, so that we would be able to find a better cost usage function, which is the purpose of this dissertation. However, there are other variables that could add extra cost, which would be not considered due to their lower and more complex effect, such as the financing system, which considers extra costs due to interest payments; and the taxes and fees, which include taxes on vehicle sales as well as any recurring annual costs and would heavily depend on the state.

There is another cost not directly affected by the usage accumulated on the vehicle, which is the labor or time cost of the drivers. As such, it will not be considered for the TCO analysis. It will be later added as a cost depending on the time operation of the vehicles during their trips, in the simulation of the impact and interactions of usage cost functions in shared mobility systems.

Cost Function Variables

We analyzed the vehicle cost information obtained from the Edmunds database, for each one of the most important vehicle types considered from the NHTS, and for several of the most important vehicle models for each type from the KBB survey information. We obtained the information, and we averaged the cost of the variables for each vehicle type considered for each year of a five year period. We have added another vehicle type, electric vehicles, and have done the same process. Even if it´s not very representative in the NHTS 2017 survey, it is one of the types in the rise lately and we would include it and consider its impact in our research. Based on all this information, we created a general cost function for each vehicle type depending on the mileage.

While vehicle and fuel costs are two of the largest factors in the total cost for many vehicles, if we examine solely these two components, we might not fully capture the differences between vehicle types. We can observe that vehicle retail price is the largest cost in early years, but over a longer analysis window, recurring costs such as maintenance, repair, insurance, fuel, and others become increasingly important. As such, establishing the bases for these cost components is crucial to understand the total cost of ownership and the mileage costs in the lifetime of vehicles. We obtain similar findings in research from other studies such as done at the Argonne National Laboratories, where they focus in the particular differences of vehicles with different characteristics and powertrains. In their results they show the importance of considering similar variables, and that previous research which has focused primarily on vehicle and fuel costs, may have misrepresented differences in TCO between powertrain types (Argonne National Laboratory, 2021).

We can observe similar patterns of costs from the information extracted for every vehicle type, with particular differences in the values obtained and the distribution of costs in each case. Note that in this approach, we are translating the use over time of the vehicles to use over miles (mileage), and given the information provided, 15,000 miles per year are considered. Thus, the information is initially presented as the cost after each one of the years (Figure 24, Figure 25, Figure 26, Figure 27, and Figure 28) and will be later presented as the average cost per mile (Figure 30). These figures use fitted curves through point data.

As we hypothesized, the repairs and fuel costs increase over time, and for the same reason, with the use. The value and the speed of which it changes varies depending on the vehicle type, giving the SUV a higher cost and higher change over time, the electric a much lower value and the compact a value in between. If we analyze the values of maintenance, we observe that the information provided gives an alternated high and low value for each year. To analyze its trend, we can linearize these costs over time, and we can observe an upwards trend, similar as the rest of the costs.

This linear function is what we will use for our purpose instead of considering the nonlinear approach provided by Edmunds. Even if the costs of maintenance might be considered on alternated years, as they represent a similar value compared with the other variables considered, we think that this approach makes it easier to analyze the total value of the vehicles over time.

Perhaps the trickiest variable considered is the purchasing price and its relationship with its depreciation. While they are connected, we would not use both at the same time. The purchasing price is usually a one time or a financing cost that can be averaged through the life of the vehicle, so we could think that it is an easier cost to consider. However, at any time in the life cycle of our vehicle it still has a remanent value, depending on how much can we sell it for. Thus, the real cost of the vehicle would be the difference between the purchasing cost and this potential benefit.

From the point of view of the costs of operating the vehicle, we would be interested in an easier way, finding it through its depreciation. This cost gives us at any point in the life of the vehicle how much it is really costing us, and in a way, it already considers the difference between the cost of purchasing it and its amortization.

The main issue with the analysis of the depreciation is that vehicles depreciate a lot in the first year. Different vehicles depreciate at different rates, but in general, new cars lose about 20% of their manufacturer's suggested retail price after a year and about 60% of in the first five years. The percentage of depreciation the following years is much lower and tapers off at a lower rate. This means that, if we have a look at the yearly cost graphics (Figure 24 - Figure 28), besides the first year, we could linearize the depreciating cost of the vehicles, which would give a decreasing line with a low slope. This shape of the depreciation appears is very similar with any vehicle type.

It is important to mention that depreciation is a value that initially would not go to zero as vehicles keep depreciating during its lifetime. However, the total cost of the depreciation can never reach the total cost of the vehicle, as this would mean that the vehicle depreciates more than its original value. This last consideration is solved in part as we consider initially a total life of the vehicles in about 200,000 miles (or around 10/15 years), and with the values considered by Edmunds and the estimations for the following years, the total cost of the vehicle is not reached.

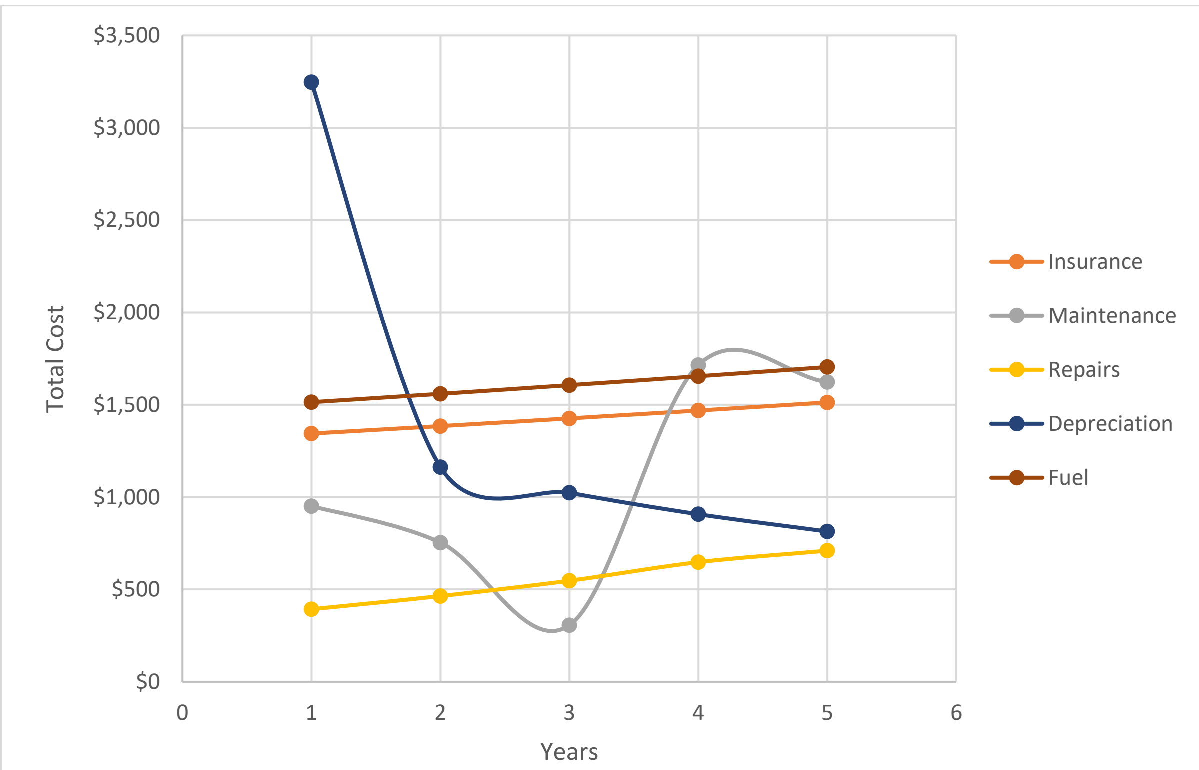

Figure 24. Yearly cost information of Compact Vehicles

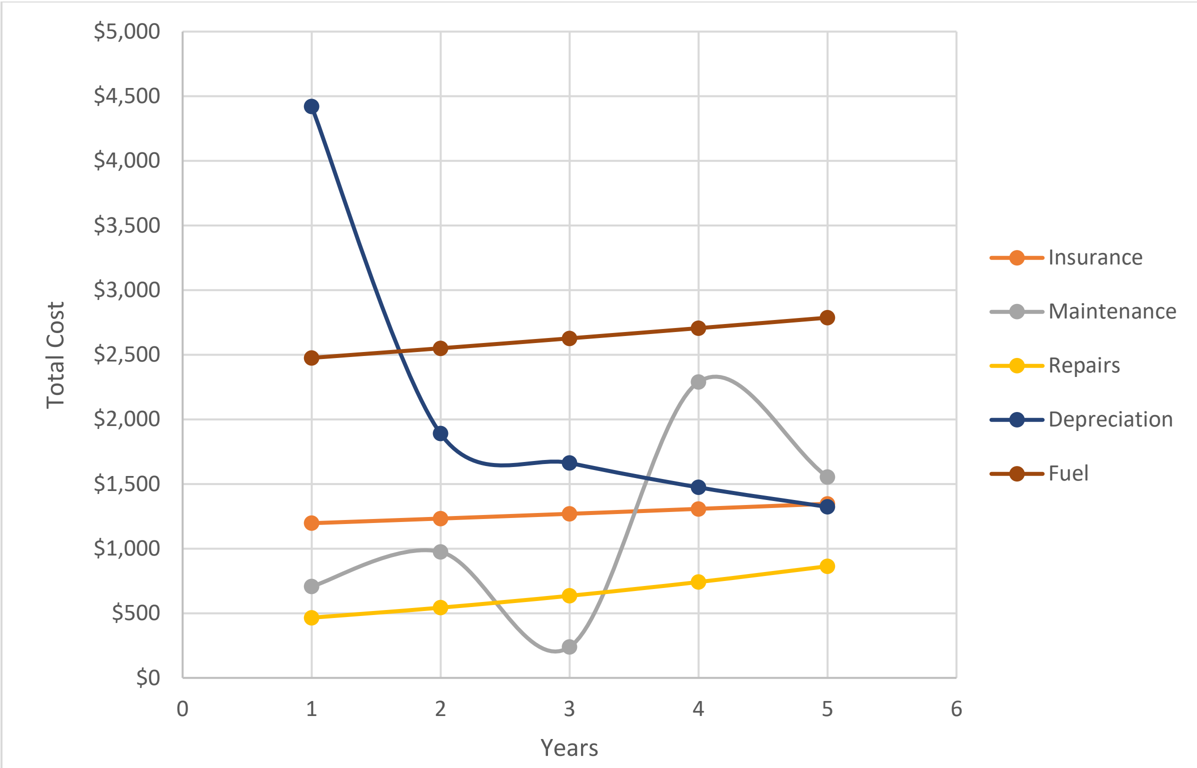

Figure 25. Yearly cost information of Van Vehicles

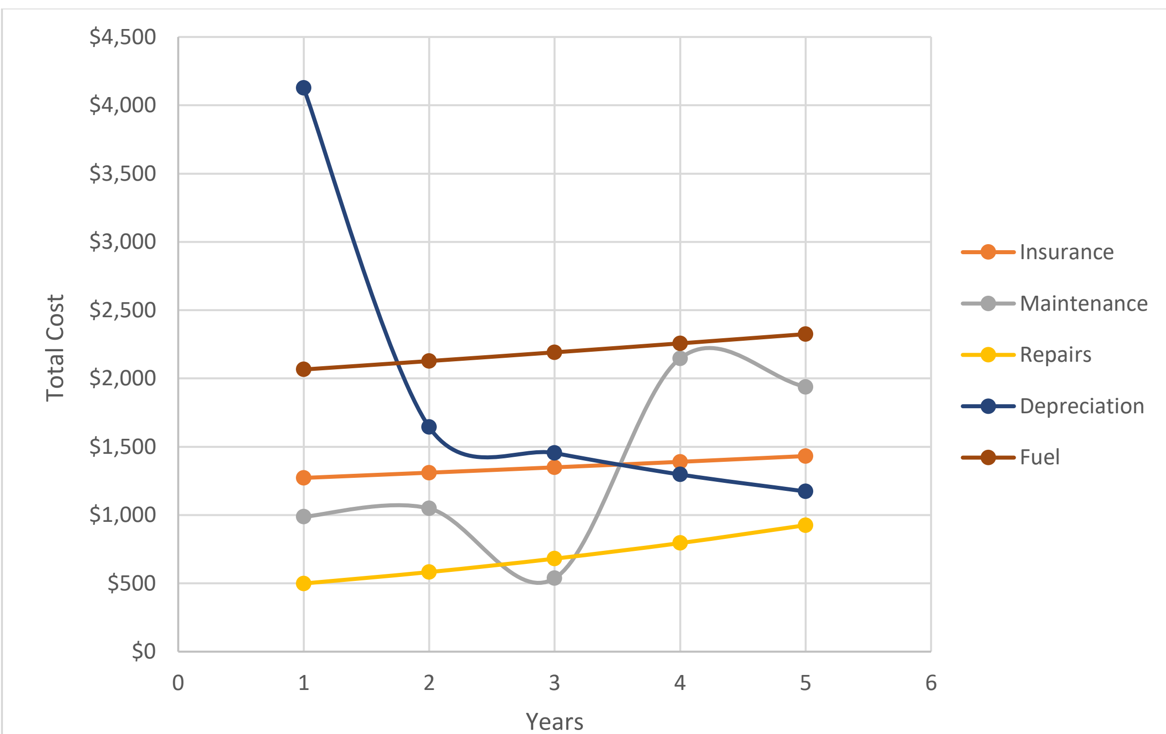

Figure 26. Yearly cost information of SUV Vehicles

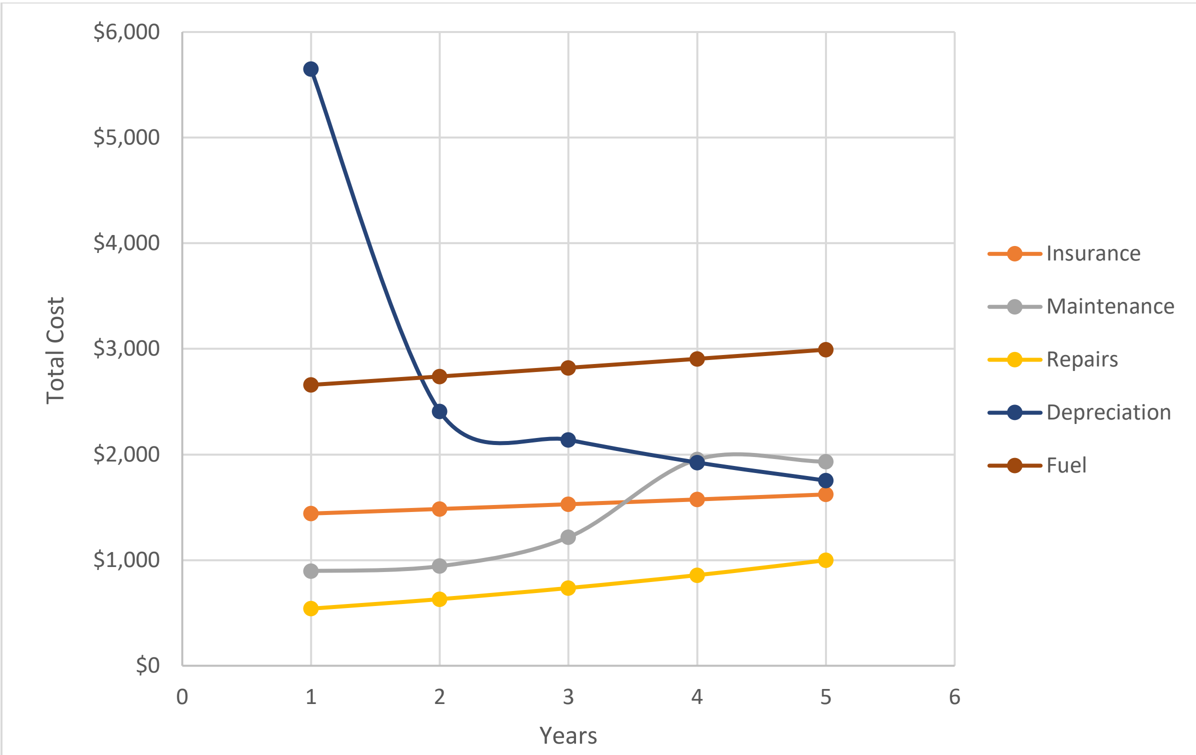

Figure 27. Yearly cost information of Truck Vehicles

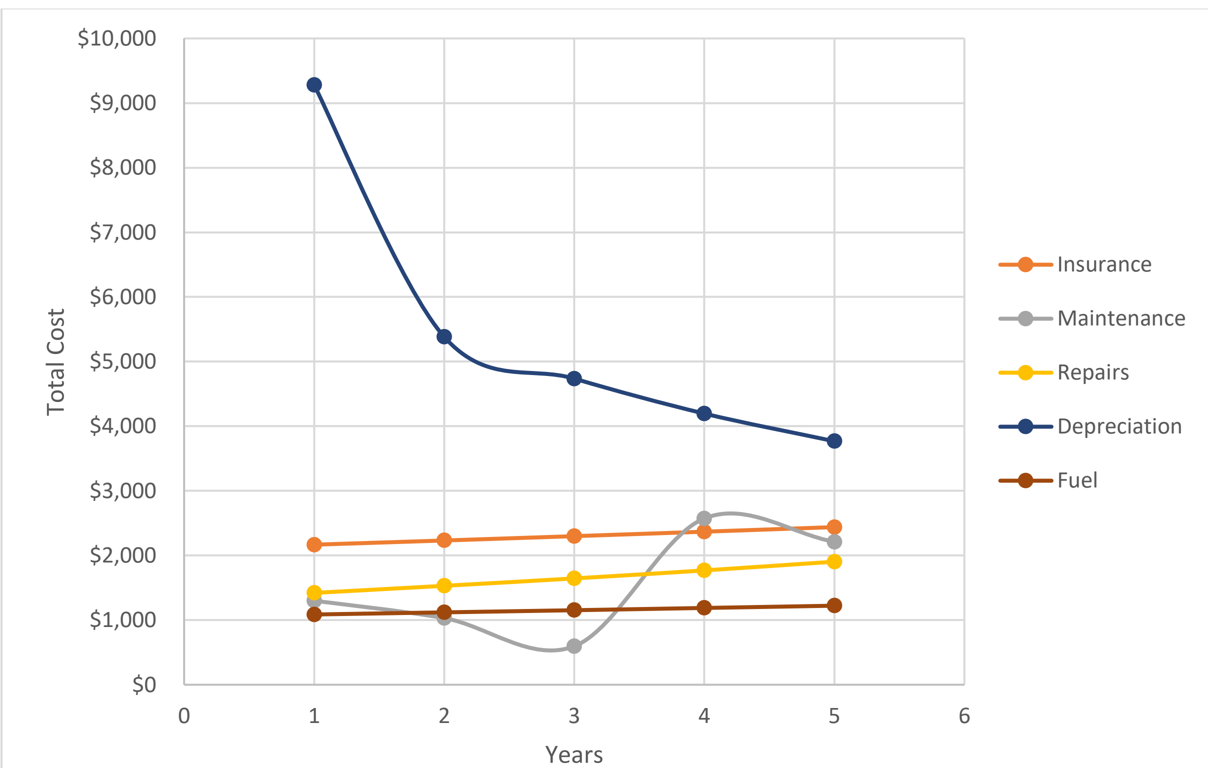

Figure 28. Yearly cost information of Electric Vehicles

There is a second issue when we consider the depreciation of the vehicles, which is that the vehicle depreciates a lot the first year, but this depreciation starts the moment the vehicle is purchased. This means that, if we tried to estimate the depreciation cost using the values obtained fitting a power function, the cost of depreciation not only would tend to infinity at time zero, but it would also surpass the total cost of the vehicle. We attempted fitting an approximation using other functions, but none seemed to adjust to the cost information well.

In addition, if we only average the cost obtained for the whole year, we will have other issues with the cost function and we would not recreate the reality, where the depreciation of the vehicle is highest, even the first months, and then starts decreasing. The solution proposed utilizes the data to generate a function that distributes the cost for the first year and linearizes it considering the cost of the second year, giving as a result a decreasing linear function with an initial very high slope which then reduces to a much lower slope value.

Our purpose is to estimate changes in costs; however, price can change because of general price inflation, and we would want to account for these changes. To avoid mistaking price inflation for changes in actual cost, we want to express and compare all cost estimates in terms of the same amount of money per unit of output. With this purpose we can make use of Implicit Price Deflators (IPD). Then, we designate a year as our target for the target price year for our outcome, and the dollar values expressed with respect to this year are called "constant" or "real" dollars because they are based on prices at a constant output level. In this analysis, we use the year 2021 for all costs and convert all prices to 2021 dollars.

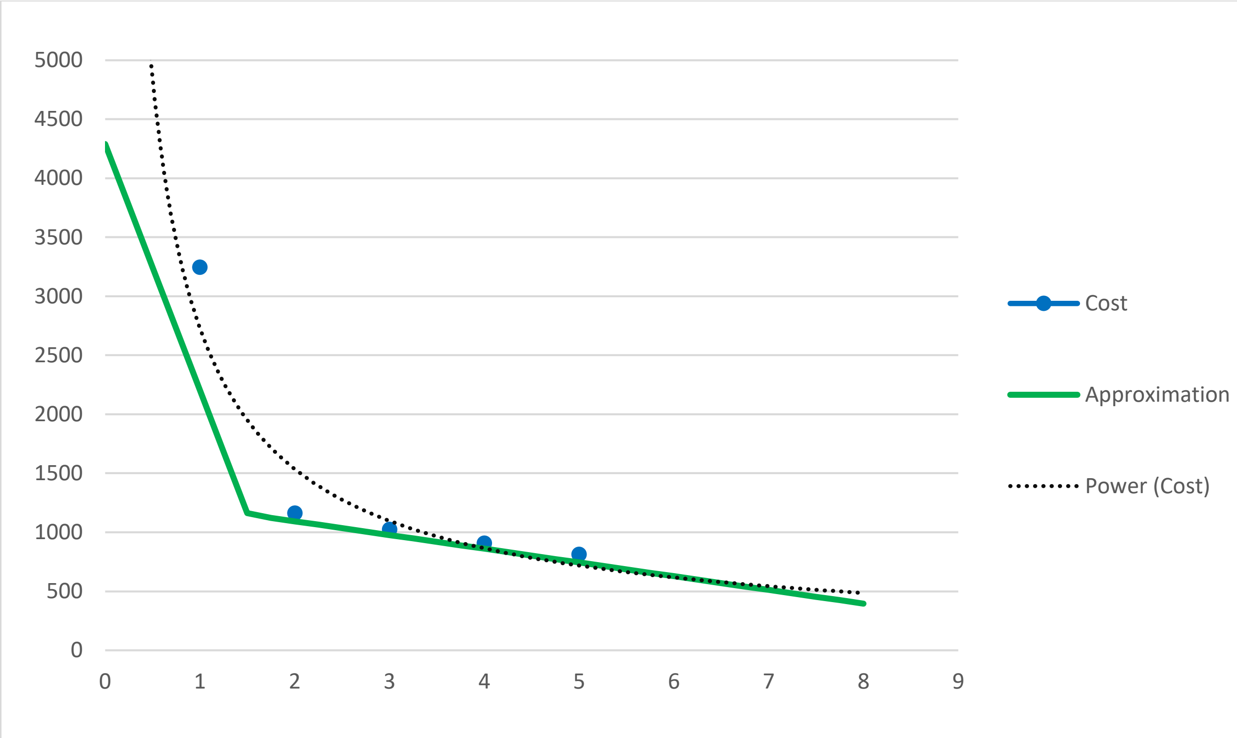

Figure 29. Depreciation of a compact vehicle with the original cost (blue), linear approximation (green) and fitting (dotted black)

We use the Gross Domestic Product Implicit Price Deflator from the U.S. National Income Product Accounts compiled by the U.S. Bureau of Economic Analysis (BEA) to estimate the rate of inflation. This expresses the yearly change in the relationship between prices and output. Thus, we can pick a single price with the corresponding output year upon which we would base all of our cost estimates, and then convert all estimates to this particular year. In this analysis, we find a total cost of ownership based on the vehicle costs and converting the value to the corresponding year. This is presented in the Equation 1, where i is the year considered, N is the total length of the analysis window, d is the discount rate due to inflation, and C_i represents the cost in year i.

$$TCO = \sum_{i}^{N} \frac{C_i}{(1+d)^i}$$

Equation 1

With this information we can obtain the TCO of the vehicles in our system. However, in terms of the full cost of the vehicle, at this time there are no models that consider a function cost for the life cycle of a vehicle in this new situation of shared mobility. From all the cost of the vehicle, we will focus on the cost during its use, because it is the characteristic most affected by any change of ownership and usage paradigms. The importance of considering life cycle models is that we can generate a usage cost model that nobody has considered for a new transportation situation. We should consider or simulate the significantly increased daily usage under the new mobility options in which this model is based, include the variables that would the strongest effect on the model.

Usage Cost Function

There are many variables that could be involved with the usage of vehicles and the associated costs, however, given the information obtained from the Edmunds database, the variables selected that would seem to be the ones affecting more the vehicle total cost where the depreciation (includes the purchase cost), insurance, maintenance, repairs, and fuel.

Parking can also be significantly affected by the use of AVs. As the vehicles can keep going around (cruising aimlessly), the cost of the parking could change depending on different scenarios. Depreciation is separated as a fixed cost because it can be used to show the cost of purchasing the car and how it is affected with time. It would also be limited by the constraints of the network and control of the fleets and vehicles. Finally, travel time is also considered to be important for the optimization, however, it would be added after the simulation, to compare the total cost of different scenarios and to analyze the difference between driving or being a passenger on a vehicle.

The resulting cost function is a linear relationship between these five variables (Equation 2). Between them, the one with the highest importance is the depreciation, because it is the one most affected by the usage of the vehicle and would have a higher repercussion in its cost. We also give it the terminology of fixed cost because it is more intrinsic to the vehicle type and might not be as affected by the individual characteristics of the vehicle model and make, like the other variables will.

$$Usage\ Cost\ function: \sum_{n}(C_n) = \sum_{ijt}(C_{f\ ijt} + C_{v\ ijt})$$

$C_{f\ ijt}$ = Fixed cost (Depreciation cost of the vehicle)

$C_{v\ ijt}$ = Insurance + Maintenance + Repairs + Fuel

Subject to network and control contraints

For vehicle *i*, from fleet *j* and time *t*, for all *n* vehicles in the system

Equation 2

With the original information from Edmunds of costs as a function of the age of vehicles (years), we have adjusted that function to consider the use of the vehicles, the miles associated, as the independent variable, assuming a ratio of use of 15,000 miles per vehicle per year (the ratio broadly used and also assumed by Edmunds in their data presentation).

Moreover, as the cost information was for the year, we averaged that information for the 365 days and assumed an average value for the distribution at the middle point of the year, in order to obtain the linear function.

We have extrapolated those results to consider a higher use of vehicles, to consider the effect of the increased use in ridesharing vehicles, which is the focus of this research. The costs functions presented have a very similar shape due to a similar distribution of the cost information. The costs functions can be described as a piecewise linear function composed by two continuous parts (Figure 30). Initially all the vehicles have a high cost due to the high initial cost of the purchase, and how all vehicles are highly depreciated the first years. Then, the depreciation decreases, and the other variables start having more importance. As a result, we have a very similar shape across all vehicle types, with a highly decreasing slope, an inflexion point around 22,500 miles, associated with the 2 years use and then a positive slope.

What is especially different for each vehicle type would be the costs for different miles of use and the slopes of the two parts. The regular car is the cheapest option during all their lifetime, then we have the SUV and the Van, with similar values and crossing due to differences in terms of cost, maintenance, and repairs, and finally the pickup. The electric vehicle starts as the most expensive option, with the highest initial purchase and consequent depreciation. However, the low costs associated with maintenance and repairs, make them have a very slow slope in the increase of cost after the inflexion point. This makes the cost of the electric vehicle cross the other cost functions each one at a different point in their lifetime, being the second lowest cost per mile option at late stages. Furthermore, these findings combined with the results from other studies increasing the total mileage in the lifetime of electric vehicles, and the potential reduction in the production of electric and autonomous vehicles, make them an interesting option to consider in the near future.

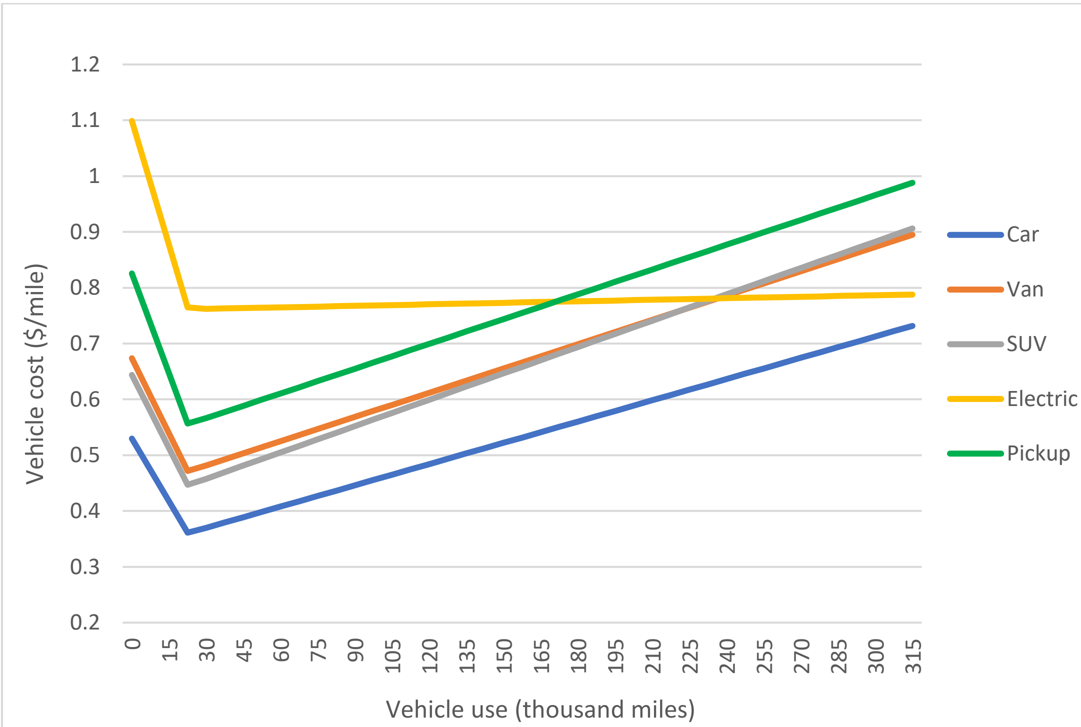

Figure 30. Vehicle type cost function distribution for a higher lifetime cycle scenario

Implications

Current and future frameworks, simulations and optimizations would benefit of this type of analysis. As they include more tailored cost functions for vehicles, they would be able to better assess the impact of new mobility systems and consider how vehicles are affected. This type of cost const functions can be included in simulation frameworks where not only the travel time of vehicles is considered, but also their operational cost. It can be particularly important in optimizations where a company would be interested in reducing the cost of using its vehicles and how to better allocate them. Moreover, with more information from the users, we would be able to determine the type of vehicles that they need, or the type of vehicles that a fleet of shared vehicles would be better to supply certain demand. These vehicles would adjust better to their needs, depending on the use that they need of a vehicle, the occupancy, the type of trips and even their sharing options.

It would also help from the users' point of view. If we can obtain a better estimate of the cost, we can present the user with the alternatives that would be more efficient to them. This type of analysis opens the door to mobility service scenarios where a person has different options for their trip, and we would be able to present them the one that better adjusts to what they need, even if they own a vehicle or not. With them, there might also be a change in the perspective towards having a vehicle, and a potential change in the ownership paradigm, which would be further explained in the chapter 4 that give results on the interactions between elements in the framework presented in this dissertation.

Using this cost function as an objective function in the optimization in simulation frameworks with shared transportation systems is something that would be further explained in the chapter 4, in particular, the implementation within the framework presented in this dissertation. However, it is important to notice how by considering the cost of vehicles as part of the formulation, we can have situations where several vehicles can be presented as options for different trips.

Initially, users, or even companies, would like to select the newest vehicles, because their operational costs should be lower at the start. However, due to the findings on the initial high cost of the depreciation, the newest vehicles would not be selected as the best alternatives for having a higher cost per mile. As they are more used, their cost reduces, and they would be selected more. Finally, as the vehicle accumulates many miles, they will start to be used less as their cost would be higher than newer vehicles. This means that we would have a curve of vehicles chosen as mobility alternatives that is inverse to the vehicle cost: very low the first year, the very high, and then slowly decreasing.

For this process of selection of vehicles, we are not considering personal preference or comfort that people might have on new vehicles compared to older ones – an issue that would affect the decision process. However, as commented earlier, we would expect a higher usage of vehicles with shared mobility systems. This increased use would reduce the total life on vehicle. Thus, the potential impact of vehicle age in the decision process of users, and therefore, minimizing any changes in the selection of vehicles. The process of selecting an alternative from a shared system is further explained in the chapter of interactions.

In this type of scenarios where we have share mobility systems is where this type of cost considerations is particularly important. While we have already commented the importance of the total costs of vehicles during their lifetime, not only to understand how much they can cost but also to be able to fully compare different models with the TCO analysis, considering the cost per mile function depending on the usage of the vehicle would be more useful. TCO analysis compares the cost of using a vehicle during its lifetime, however, there are many situations where a vehicle might change of owner or a vehicle that might not be totally used. We would like to compare the cost of used vehicles and what is left for the rest of their lifetime, and this might not be fully obtained from TCO analysis, but we would be able to compare it with the usage cost function.

In particular in the scenarios that we are considering where shared mobility systems would be more predominant, we would have situations where not only users but also companies might own vehicles, and they would be particularly interested in the usage range where vehicles can be the most profitable. This area is the part of the cost function commented where they have the lowest operational cost around 22,500 miles, until some point around 180 thousand miles where they start having a higher cost too depending on the vehicle type.

It is important to notice that the final objective of using usage cost functions would be a situation where there would be access to all the information about all the vehicles, and we could not only generate vehicle type cost functions, but also individual cost functions for each one of the vehicles in the network. However, at this moment it is difficult to get this type of information, and the analysis presented uses cost data for the most representative vehicle types. At the same time, this change in the ownership of vehicles might affect the sales of car companies who may then have the depreciation worked into the price of the vehicles to counter this, which in turn would affect the cost function considered. This circle interactions, however, is not being considered as a part of this dissertation, due to uncertainties on the car manufacturers' pricing decisions. In following chapters, the direct interactions of impacts of the cost function in a shared mobility system scenario will be analyzed, and a shared system simulation system where each vehicle will have its cost function depending on its type will be presented.

Discussion

In this chapter, we have presented the current problems in terms of transportation costs and congestion. We have presented a possible alternative based on shared and/or autonomous vehicles and how it could bring other challenges. In this situation, we focus in modelling the interaction of these new mobility systems with the corresponding supply and demand, which will have their own interactions. These relate to the new price-cost paradigms, given the new ownership situation associated with the change of mobility and the traveler's usage pattern. We have also presented the methodology that we will follow to analyze presented and more complex interactions. We have shown the importance of this type of study and the analysis with the initial considerations of the cost per mile of vehicles.

In following chapters, we present the framework that we have developed and the test simulation that we will analyze. We are considering a representative group of different types of vehicles, where we can simulate the mobility of a small network and analyze their increased usage. With that, we can consider initial estimates of their cost and by obtaining their mileage we can obtain how much they cost to the system. We can also notice that, depending on who is making the decisions and what is his final objective we could have different potential scenarios. We could have the public administration controlling a fleet of SAVs trying to minimize the cost and offering a good mobility option, or private companies trying to minimize the cost and maximize their revenue. The final objective of this dissertation is to simulate these vehicles to be able to optimize the transportation system with a new cost function that considers the increased usage of vehicles.

CHAPTER 4:
Interaction Framework and Analysis

Introduction

Up to this point, we have focused on situations where SAVs could cause improvements, and we can achieve this by creating fleets of shared and/or autonomous vehicles that can be optimized much better. With that we will be able to analyze more advanced situations and different scenarios. By considering their cost, the number of vehicles to serve a demand can be reduced and this would increase the usage of the vehicles (their mileage). This would in turn reduce the life of the vehicles used, which is a detail that current optimization models do not properly account for. By creating a cost function for each vehicle, we can consider the individual characteristics and update them as they are used. However, this brings new situations in which we go from a centralized optimization system to a more decentralized situation in which we can obtain information from the point of view of the vehicle. By improving the average cost model, we could do optimizations individually for each vehicle's operation so that every car does it by itself.

Other aspects that we are considering with this optimization are the interaction with the user and the possibility of having multiple agencies or modes (Nivola and Crandall, 1995). This algorithm is based on the point of view of the vehicle; thus, it is based on obtaining the minimum cost for the system. This, however, might not yield the best result in every aspect. By minimizing the cost, we can affect the possible demand that matches it, meaning that the demand might reduce given the characteristics of the system. To solve this issue, we can include some rules and elements in the optimization by combining the cost function with the user cost, such as adding a waiting cost or the fare of the system. Eventually, if we see that the fare is too high and the demand is being reduced, the optimization will need to iteratively adjust the variables and bring the system to a demand-cost-supply equilibrium.

The optimization is made so that we could have different fleets in the system. However, if we are considering an individual optimization at a car level, every user should be able to use the same vehicle with different fleets, or every vehicle could potentially be associated to multiple fleets (the same way that right now drivers on transportation companies switch between Uber or Lyft depending on the situation). Such possibilities have not been discussed in the transportation literature, to our knowledge. This is also linked with new systems that consider mobility services and mobility portfolios (An, 2019). The cars would be owned by a fleet manager and the mobility service providers belong to another company, so that each car can optimize by itself.

The advantage of giving each vehicle a cost function that can be used to optimize the system is that it is possible to individualize how much each car costs to the system, and with simulation we can update each one of them. Also, by having full information about the system, we would also be able to give a more realistic cost value of the vehicles. However, if there is an uptick of demand in some area of a city, many more vehicles would want to go there, to get some benefits and minimize their cost, and this could generate some clusters of vehicles. Some options to avoid this problem could consist of adding a constraint or penalizing AVs that “congregate” for a certain time period. This line of thinking can lead to a two-level optimization in which we would have a centralized optimization of the vehicles considering the demand and the minimization of the travel time to each pickup location; and also, a distributed optimization model for each vehicle of the system, where each vehicle has its own cost function that can report to the fleet operator.

One of the main objectives of this dissertation is the generation and testing of a framework to analyze the interaction between supply, demand, and pricing structures in new ridesharing scenarios. In this section, we will present this framework along with the formulation needed to consider cost and pricing structures, as well as the previous ideas in terms of vehicle characteristic distribution. First, we will present the diagram of the framework that we are proposing and the characteristics of all of its elements, then we will comment the importance of pricing schemes and what should be considered in this type of scenarios, and we will finish with some behavioral considerations that might affect our mobility system.

Analysis Framework for SAV Systems

The rise of the sharing economy has led to the development of the well-known concept of Smart City, where people can move around it by making use of an integrated shared transportation system. The objective of this research is to analyze the changes in the traveler's usage with a new cost function that also considers different ownership paradigms, and how their interaction can affect new mobility systems of shared and autonomous vehicles, which can also include systems of fleets of vehicles. We would need a proper framework that can analyze these new situations.

Currently, there are many algorithms for cost optimization and fleet management but none of them considers the efficiency of the system using the total cost of the vehicle during its life. Some of the reasons are that in the current situation, vehicles have a long life cycle, and the impacts of the usage in TNC companies have not totally been analyzed; also, in current car services the cost of the driver (or their earnings) are too high compared with the rest of each individual cost. But with SAVs this situation could change, instead of one driver per vehicle we would have a reduced number of vehicles for the same demand. We could also have a smaller number of people supervising a bigger number of vehicles and the increase usage of cars could help on determining the most important variables that would be affected by the mileage, thus, increasing more the cost.

The purpose of this framework is to consider the interaction between supply, demand, and pricing structures in new shared-ride mobility situations. It considers a situation where the point of view of the vehicle would have more impact on the cost and use of the service. As a result, we would transfer the transportation optimization focus from a centralized system to a more decentralized scenario, where vehicles have more importance by themselves, and we should get more attention to their increasing use and associated cost. The final objective is to analyze the interaction of all the elements from each SAV scenario to present a better mobility alternative with a reduced cost and more durable system.

Vehicle-Usage-Cost-Based Framework

The framework presented (Figure 31) is based on the vehicle usage cost associated to the vehicles on the network. It is divided into five different blocks that cover all the steps of the generation, simulation, and analysis of the mobility of people in a network. It is based on a heuristic optimization where for each situation some candidate rules are set and compared. Then, the parameters of each scenario are analyzed to improve the rules and determine what kind of operation is more optimal for each shared system considered.

The first step analyzes the trip and network information from the demand and supply databases considered. It also includes the pricing scheme considered for that mobility scenario. This information is fed into a ridematching algorithm, where riders are matched with drivers following an optimization to improve the system. Then, the new trip information is formatted to be used in an agent-based simulation called Polaris, where we obtain all the results from the mobility scenario. Finally, we use this new data to update the characteristics of vehicles for the following ridematching and step of the optimization, and we analyze the benefit and cost of the mobility system, given the usage obtained from the vehicles.

All the elements of the framework are coded and/or integrated using Python, which is an interpreted, object-oriented, high-level programming language with dynamic semantics. It is a common programming language which allows us to combine and communicate different formats and processes. In particular, the databases are analyzed in SQL format, then the information is treated, and trips are matched with Python. The Polaris simulation is coded in C++ but integrated in the Python code, which updates the vehicle information and finishes the system analysis in the same language.

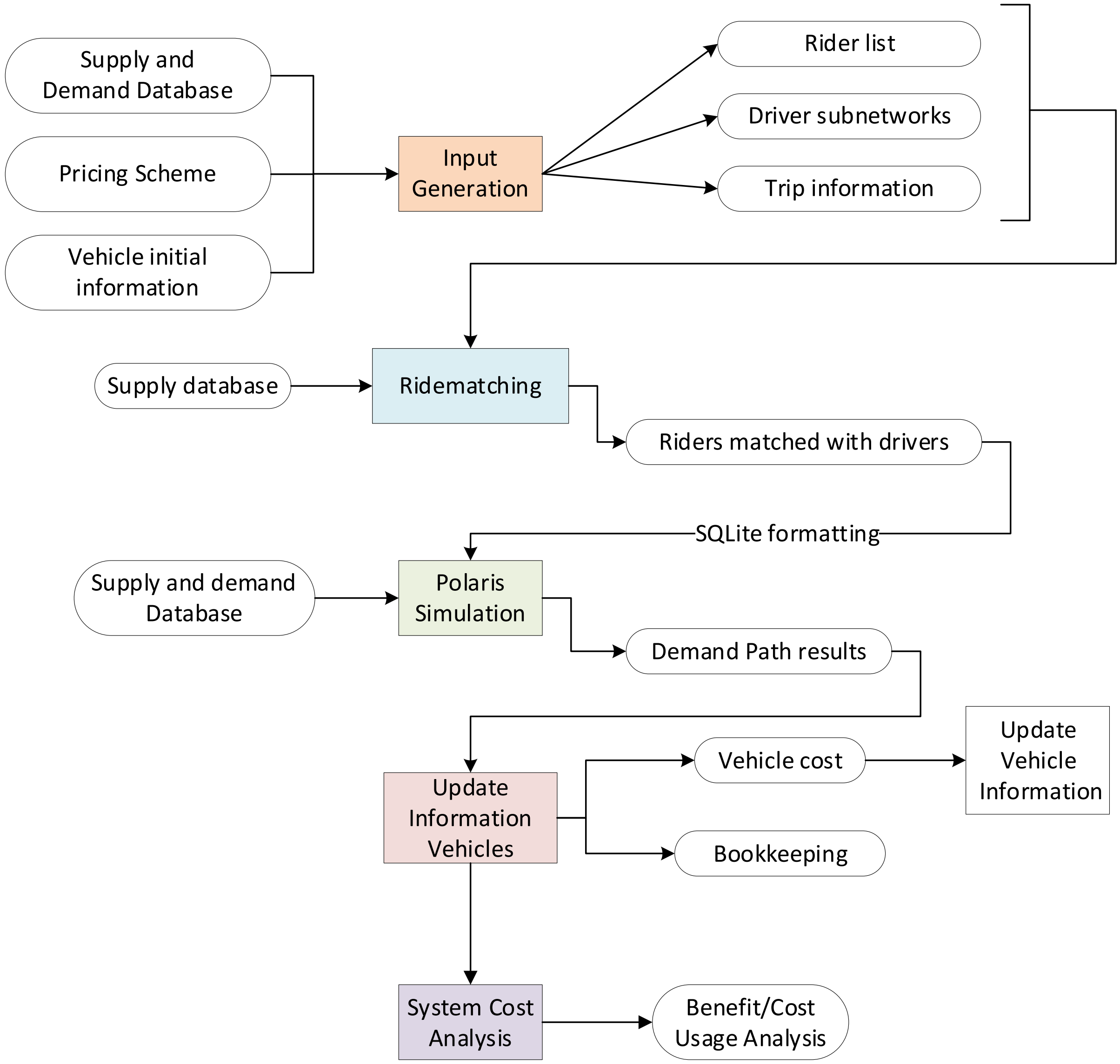

Figure 31. Vehicle-Usage-Cost-Based Framework

Input generation

The role of this module is to preprocess the trip and network information to make it suitable for the ridematching and simulation steps. The information is treated to generate trips for each agent from the database. Each person is divided into a subcategory where they can be a part of the ridesharing system and attempt to not use their personal vehicle (rider) or choose to use their own vehicle for their trip and might be part of the sharing system driving other riders (driver).

The objective is to limit the size of the accessible network for the system participants to reduce the peer-to-peer ridematching computational time. This technique used proposes an Ellipsoid Spatio-Temporal Accessibility Method (ESTAM) that reduces the size of the original time-expanded network for each system user, considering reachable spatiotemporal links within their respective travel time windows. In the first phase of framework, we applied the ESTAM method on an abstract network (algorithmic details can be found at Masoud and Jayakrishnan in 2017).

The ridematching algorithm

One of the essential concepts through this dissertation is the peer to peer ridesharing system. It is the most comprehensive and relaxed type of ridesharing systems where people can join as either mobility providers or receivers. People not only utilize mobility services as users, but also provide themselves with their vehicles as shared-ride drivers or offer their cars as carsharing providers. People can also be allowed to easily shift their travel status, which can provide more opportunities for them to get matched.

Our analysis is performed on an abstraction of the real network where the origins are destinations are defined by nodes, connected by links, and people travel to develop an activity at a location. In the real world, some transportation services share a vehicle network, but other modes such as metro, rails and walking share a physically separate network, which is not part of the vehicle network. With this in mind, a multi-layered transportation system was proposed to analyze different types of transportation, where each one of them is considered in a separate layer (Nam et al., 2018). Without any loss of generality, we assume that all trips originate and terminate at these nodes which can also be considered as go-points (Masoud and Jayakrishnan, 2017). The shared autonomous fleet vehicle network is designed for a system where they start their trips from a depot and move between these go-points. We assume that SAVs have the same features as in the vehicle network and would be considered in a separate layer where the nodes would be referred as stations.

We build a time-expanded network for system of the network. This means that we have nodes which have both time and location aspects. In addition, we discretize the study time span into a set of indexed time intervals of a small duration Δt, expected to be 5 minutes or less (we use 1 minute) so that time-dependent travel time matrices can be used for analysis. In this network, each node n_i is considered as a tuple (t_i, s_i), where t_i is the time interval during which a user may be located at station si. In turn, a link can be represented as a tuple of nodes $(n_i, n_j) = (t_i, s_i, t_j, s_j)$ (Masoud and Jayakrishnan, 2017). It considers a time-expanded network, as we can see in the figure 32.

A benefit of the peer-to-peer ridesharing and ride-matching mechanism is that it is flexible to operate in a collaborative multimodal transportation system that includes various mobility services such as shared-ride providers, bike, scooter, walk, public transit and even shared autonomous fleet vehicle and it can easily link mobility services providers and service users. By dividing people into rider and driver groups and matching, we would get people who keep being matched, while there are others who do not. Thus, this problem can be solved by formulating a peer-to-peer (p2p) ridematching problem of matching paths in a time- expanded network.

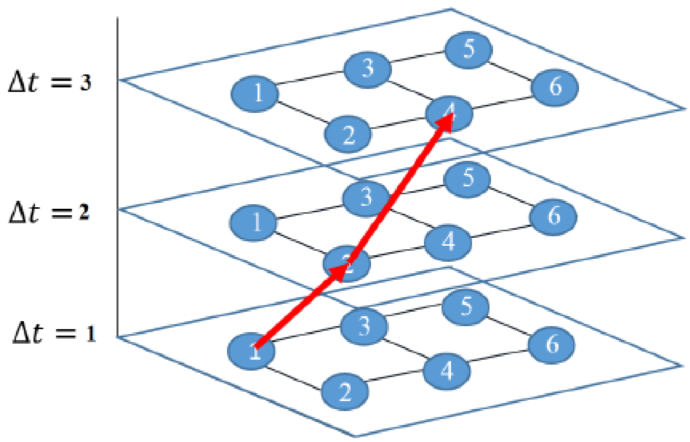

Figure 32. Links on a time expanded network (Masoud, 2017)

The goal of the p2p ridesharing system is to match as many participants as possible in real-time. In this context, Masoud and Jayakrishnan mathematically formulated and solved a real-time p2p ridematching problem with a dynamic programming approach. The optimization is then solved using an algorithm that takes riders to their destination by optimally routing drivers. These itineraries will have to comply with the characteristics of the vehicles and the travel specifications of the riders, and the algorithm will optimize the matching rate of riders on drivers. One of the assumptions they made is that origin and destination are fixed variables, where OS_r, OS_d, DS_r, and DS_d represent origin and destination go-points for both riders and drivers, respectively.

Equation Set 3 shows the original ridematching problem formulation which uses four binary decision variables set in Equation 4. Naming the objective function and the constraints of the optimization system in Equation Set 3 as (a) through (m) in order, (b-h) refer to the routes of drivers inside the network. Equation Set 3 (b-d), origins (b) and destinations (c) of drivers for each trip, flow conservation (d), limit on the total travel time (e), the constraints of the riders (f-h), analogous to Equation Set 3 (b-d), and the capacities and transfers (i-m), maximum rider's travel time (i), capacity of the vehicles (j), and the total number of transfers (k-m).

The benefits of this ride-matching algorithm are that it is an idealized optimization that uses coarser time steps and has fixed inputs that can be optimized in detailed subsystem optimizations, for instance, optimizations of micro-transit, signal systems or ride-share vehicle selection, with some appropriate network structure specifications (dummy-links, inventory links, etc.). Hence, it is especially useful in our case because we can adapt it to optimize different situations of objective/cost functions and connect it to more elaborate subsystems that will serve as inputs for the general ride-matching optimization.

Because of that, we can analyze complex scenarios of multiple modes of mobility (as in the mobility portfolios mentioned above) by translating them into a temporal-spatial ride-matching optimization. However, given the complexity of these situations, the way to handle these scenarios will be an implementation of the optimization in a decomposed fashion. This would mean that we would have detailed subsystems feeding their results as inputs for the ride-matching algorithm.

$$\text{Max} \quad \sum_{r \in R} z_r - \sum_{r \in R} W_r \sum_{d \in D} u_r^d$$

(a) $$\sum_{\substack{\ell \in L: \\ s_i = OS_d; t_i, t_j \in T_d}} x_\ell^d \quad - \sum_{\substack{\ell \in L: \\ s_j = OS_d; t_i, t_j \in T_d}} x_\ell^d = 1; \ \forall d \in D$$

(b) $$\sum_{\substack{\ell \in L: \\ s_j = DS_d; t_i, t_j \in T_d}} x_\ell^d \quad - \sum_{\substack{\ell \in L: \\ s_i = DS_d; t_i, t_j \in T_d}} x_\ell^d = 1; \ \forall d \in D$$

(c) $$\sum_{\substack{t_i, s_i \\ \ell = (t_i, s_i, t, s) \in L}} x_\ell^d \ = \sum_{\substack{t_j, s_j \\ \ell = (t, s, t_j, s_j) \in L}} x_\ell^d; \ \forall d \in D, \forall t \in T_d, \forall s \in S \backslash \{OS_d \cup DS_d\}$$

(d) $$\sum_{\ell \in L} (t_j - t_i) x_\ell^d \leq \frac{T_d^{TB}}{\Delta t}; \ \forall d \in D$$

(e) $$\sum_{d \in D'} \sum_{\substack{\ell \in L: \\ s_i = OS_r; t_i, t_j \in T_r}} y_\ell^{rd} - \sum_{d \in D'} \sum_{\substack{\ell \in L: \\ s_j = OS_r; t_i, t_j \in T_r}} y_\ell^{rd} = z_r; \ \forall r \in R$$

(f) $$\sum_{d \in D'} \sum_{\substack{\ell \in L: \\ s_j = DS_r; t_i, t_j \in T_r}} y_\ell^{rd} - \sum_{d \in D'} \sum_{\substack{\ell \in L: \\ s_i = DS_r; t_i, t_j \in T_r}} y_\ell^{rd} = z_r; \ \forall r \in R$$

(g) $$\sum_{d \in D'} \sum_{\substack{t_i, s_i: \\ \ell = (t_i, s_i, t, s) \in L}} y_\ell^{rd} = \sum_{d \in D'} \sum_{\substack{t_j, s_j: \\ \ell = (t, s, t_j, s_j) \in L}} y_\ell^{rd}; \ \forall r \in R, \forall t \in T_r, \forall s \in S \backslash \{OS_r \cup DS_r\}$$

(h) $$\sum_{d \in D'} \sum_{\ell \in L} (t_j - t_i) y_\ell^{rd} \leq \frac{T_r^{TB}}{\Delta t} \forall r \in R$$

(i) $$\sum_{r \in R} y_\ell^{rd} \leq C_d x_\ell^d; \ \forall d \in D' \forall \ell \in L$$

(j) $$u_r^d \geq y_\ell^{rd}; \ \forall r \in R, \forall d \in D, \forall \ell \in L$$

(k) $$u_r^d \leq \sum_{\ell \in L} y_\ell^{rd}; \ \forall r \in R, \forall d \in D$$

(m) $$\sum_{d \in D} u_r^d - 1 \leq V_r; \ \forall r \in R$$

Equation Set 3 (a-m) Ride-matching algorithm optimizing the matching rate subject to demand and network constraints (Masoud, 2017)

$$x_\ell^d = \begin{cases} 1 & \text{Driver } d \text{ travels on link } \ell \\ 0 & \text{Otherwise} \end{cases}$$

$$y_\ell^{rd} = \begin{cases} 1 & \text{Rider } r \text{ travels on link } \ell \text{ with driver } d \\ 0 & \text{Otherwise} \end{cases}$$

$$z_r = \begin{cases} 1 & \text{Rider } r \text{ is matched} \\ 0 & \text{Otherwise} \end{cases}$$

$$u_r^d = \begin{cases} 1 & \text{Driver } d \text{ contributes to the itinerary for rider } r \\ 0 & \text{Otherwise} \end{cases}$$

Equation 4. Binary decision for the p2p ridematching problem (Masoud, 2017)

In order to analyze the interactions between the elements of our framework, in our formulation we modified the original ridematching problem to account for the vehicle usage cost function generated to consider the increase of usage of vehicles and their heterogeneity of characteristics and costs. This function will be used to optimize the cost of the transportation system in a new situation, and for that, it will be implemented as an objective function in the ride-matching routing algorithm formulated by Masoud, 2017. Instead of using the driver decision variable we can redefine it to denote a vehicle type assigned to a driver. We can consider different vehicle types and models such SUVs, electric vehicle, 2-seat door vehicle, autonomous vehicles, etc., and with that we can include a vehicle cost based on the vehicle usage cost function described in chapter 3. The formulation used to describe this optimization would be further described in the following section and in the system cost analysis section.

With this information we can calculate the minimum vehicle trip cost associated to each shared mobility provider. Note that in the p2p ridesharing system, we aim to solve the ridematching problem which finds the optimal solutions for using the vehicles. Once people are registered as shared drivers, they cannot find a rider who can optimize their path. However, every rider might have a potential group of vehicles and/or drivers who can optimize their path. In practice, the optimization imitates a real-time scenario, for individual riders, to select the best possible vehicles and/or drivers for them. This type of optimization might have certain implications. It would have to be based on the individual's objectives and not any system objectives such as overall costs or matching ratio. In traditional transportation planning we have the optimizations based on system optimum and user equilibrium, where the system objectives may cause some users to be provided solutions that are not best for themselves and can lead to lack of trust in the system. Thus user-side objective such as minimum vehicle trip cost and payment are needed. However, the collective system performance with individual (distributed) optimizations does become socially beneficial with increased sharing of resources and reduced system costs, in general, as our results will show.

In this situation, the shared system provider cannot ask any rider to select an option that involves higher payment than their best option in terms of the drivers available. However, drivers who share their trips would receive a payment and thus positive utility from offering the ride. They can be asked to offer the service to a rider who is not the best from their standpoint and gives less payment than another rider. It would be also possible to introduce a minimum payment required for any driver to offer the service, but this has not been attempted in this dissertation research. The objective is to obtain optimal solutions to the use of vehicles, which as a consequence, gives cost optimal solution for the riders.

Vehicle cost usage formulation

The ridematching problem is adapted to consider for each rider the minimum vehicle trip cost. Next, we can see a description of the parameters and variables used (Table 1).

Table 1. List of parameters and variables used in the framework

L: set of links l	C: Set of vehicle trip costs c: {fixed, variable}
N: Set of nodes n	F: Set of fixed costs f: {depreciation}
Q: Set of people q	W: Set of variable costs w: {Insurance, Maintenance, Repairs, Fuel}
V: Set of vehicles v	G: Set of vehicles used
A: Set of companies/fleets a	X: Set of vehicles used for ridesharing x
T: Set of vehicle types t: {1:Car, 2:SUV, 3:Pickup, 4:Van, 5:Electric}	Y: Set of people using ridesharing services y: (Yr: riders, Yd: drivers, Yn: riders not matched)
V_t: Set of vehicles for each vehicle type v_t	U: Set of odometer points from vehicle usage u
M: Set of modes m: {ridesharing, no ridesharing}	Z: Set of iteration mileage from vehicle usage z
S: Set of subscription services s	D: Set of travel times for trips in the system (separating segments of trips if transfers) d
B: Set of Profits b of a company	H: Set of values of time for people in the system h
R: Set of revenues r of a company	P: Set of pricing values depending on vehicles p
E: Set of expenses e of a company	K: Set of iterations of the system k

In this situation we reformulate the algorithm to consider the increasing importance of the cost of the vehicles, and that the variance of vehicles and demand would increase in the future (different tips of trips or requests that should be addressed with different types of vehicles). At the same time, we maintain the constraints of the system. Given this situation we could differentiate between a system that has an overall optimization of the system, or a more individualized situation in which there are practical subsystem optimizations where each vehicle belongs to a company or adjusts depending on the moment.

Then, for each rider on a shared trip we minimize the cost of using each available ride from the list of possible vehicles ($v*$), assuming that these vehicles are associated to one of the multiple possible service providers or companies:

$$Min\ C = \operatorname*{Min}_{\forall V} \sum_{C} (c_j) \ = \operatorname*{Min}_{\forall v* \in V} \left(c_{f_{v_{atiu}}} + c_{w_{v_{atiu}}} \right) \cdot z_{v_{ati}}$$

Where similarly as described in the chapter 3:

$$Cost\ of\ any\ vehicle: c = f(mileage) = \sum_{C} c_j = c_f + c_w$$

$$c_j = f(t, u) = c_{f_{t_u}} + c_{w_{t_u}}$$

Cost of vehicle j, from company a, type, at a mileage usage step u $\left(v_{a_{t_{i_u}}} \right)$

And if we develop the formulation for the two vehicle costs considered, we obtain a cost for each vehicle belonging to each service provider, at each time step of the simulation process. This cost would be a function of the vehicle characteristics and their usage or odometer associated:

$$c_v = \sum_{C} c_{j_v} = c_{f_{v_{atiu}}} + c_{w_{v_{atiu}}}$$

$$c_{v_{atiu}} = G\left(t_{v_{ai}}, u_{v_{ai}}\right) = g_f\left(t_{v_{ai}}, u_{v_{ai}}\right) + g_w\left(t_{v_{ai}}, u_{v_{ai}}\right)$$

The cost algorithm gives a more individualized view where the objective function can be split into multiple objective functions depending on the different variables, groups of people or fleets of vehicles. The optimization minimizes the total cost by considering for each car a function cost and adding all of them (at one or separated into fleets). The whole system would still be limited by the constraints of the network and control of the fleets and vehicles. Thus, we would apply the same flow conservation, driver's and rider's routing constraints and the route connections and transfers limitations. Given the nature of the new vehicle considerations we would have to add capacity fleet limitations where $v_{a_{t_i}}$ is used as a binary decision variable:

$$Capacity\ of\ vehicles\ for\ each\ type\colon V_{a_t} \leq \sum_{V_t} v_{a_{t_i}}$$

$$Capacity\ of\ vehicles\ for\ company\colon\ V_a \leq \sum_{T} v_{a_t} = \sum_{T} \sum_{V_t} v_{a_{t_i}}$$

The rest of the formulation of the cost optimization would be further explained in the system cost analysis section. It will use the same variable inputs, costs, and formulation. The framework would be used in a higher level of optimization, and the interactions of the agents and elements of the system would be considered to optimize the rideshare providers to present a better mobility situation.

Ridematching solution algorithm

The ridematching algorithm is solved to provide with the best trip for each user of the sharing system according to their necessities, characteristics, and the possibilities of the network and services available. Then, the results of the ridematching are simulated and analyzed in the context of the vehicle cost usage framework, and this process is repeated with the objective of obtaining the best characteristics of the shared service provider. During the matching process, we assume that the users of the service want to make use of their alternative from the shared mobility service as soon as it becomes available and within their flexibility and time restrictions.

Most of the modelling of this process is done in an offline mode, where we use the information from the Demand and Supply databases to generate the framework for the shared-mobility provider system, and then make conclusions on how it would operate. The ridematching process intends to simulate a real time process where requests are considered according to the trip starting time as described in the algorithm section of the framework. The algorithm prepared for this purpose is adjusted for each scenario depending on the requirements of the shared system, whereas we are matching drivers and riders, or we are matching users to shared autonomous vehicles. It is modified to reduce the computational time needed but efficiency is not the main focus of the work presented.

Initially, we consider the riders and shared-ride drivers of the system and solve a many to one ridematching problem. The ridematching solution algorithm is based in the work presented by Masoud and Jayakrishnan in 2017. To improve the efficiency, we use the Ellipsoid Spatiotemporal Accessibility Method (ESTAM) which constructs a time expanded feasible network for the rider and the driver depending on their trips and their flexibility, where the optimal itinerary can be obtained. With that, we generate a much smaller network for each step in the ridematching. However, depending on its initial size, the number of feasible routes for each rider can still be very large. We conduct a depth first search (DFS) on the revised time expanded feasible network, to find whether drivers can serve the entire itinerary of a rider. If we do not find any, we can discard that rider assuming there to not be a match for them. If DFS finds a path which is spatially and temporally feasible we will use a dynamic programming (DP) method to find the best path for the rider, defined as the minimum travel time path based on the link travel time between nodes.

The ridematching solution algorithm is modified in each case to consider the requirements of the shared mobility provider (Figure 33). This dissertation is focused on the importance of cost considerations due to the increasing usage of vehicles in new shared mobility systems. Several distributions of vehicle characteristics are introduced, which would affect the vehicle cost depending on their use. As a result, we have modified the ridematching process to consider the mobility provider's vehicle cost in the solution algorithm.

The best path from the Dynamic Program (DP) is adjusted to consider the lowest trip cost from the feasible drivers of the DFS. This trip cost is obtained by considering the trip distance for each travel time-path alternative, and the characteristics of the vehicle associated to each driver. Each vehicle has an associated vehicle cost function which adjust the cost per mile depending on their usage status, which is updated after each use.

With this improvement, we can include a more realistic minimum cost itinerary, and we can also capture the effects of having vehicles with different characteristics and usage stages in their life cycles.

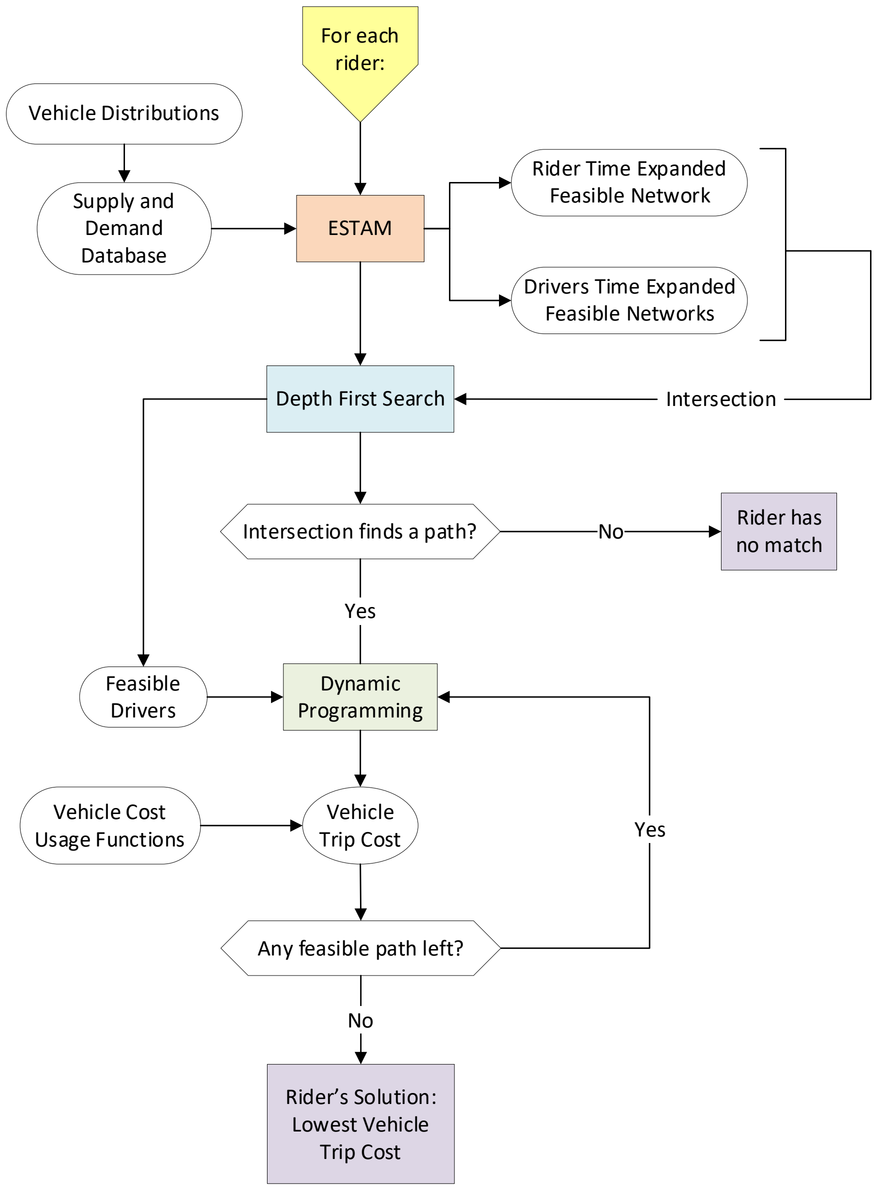

Figure 33. Ridematching solution algorithm flowchart for the ridesharing system

In the last scenario, the solution algorithm is modified to consider a system of car sharing with autonomous vehicles (Figure 34). In this case, there are no drivers, and the vehicles are waiting to either finish a trip or get matched to start a trip. Ridematching is also presented as a real time process, where users are considered according to their trip starting time. As a result, there is no need for the ESTAM to generate a set of feasible options. Instead, for each user of the system (rider) we consider all the possible AVs which can be available to serve the user. This set of AVs is formed by all the vehicles that will be available before the start of the trip (either waiting on a depot) or finishing a trip before the new one starts; and that will arrive to the pickup location during the pickup range of the rider. The pickup range considers a flexibility from the user to be picked up to improve the number of AVs alternatives, and extra time for the user to get in and out of the vehicle. If the set of alternatives for a user is empty, we consider that this rider is not matched with any AV. When the trip is finished, the AV will be available for another rider, and will wait until it can arrive to the pickup point within the pickup flexibility range of the user.

The DP in this case is applied in a similar way, considering the lowest travel time path for each rider, and the cost associated with each alternative. This cost also considers the characteristics of each AV and updates every time the ridematching is applied to consider changes that might have happened to each vehicle. Furthermore, we paid special attention to the generation of empty trips where AVs drive to pick up the next riders, and the empty miles associated with those trips are also considered in each trip cost alternative. Finally, the lowest trip cost alternative is selected and fixed for each rider, and the AV will be used for that trip. During that period, the vehicle is not available for other riders, and the new position is updated to the destination of the user's trip. The algorithm stops when all the sets of alternatives have been generated for each user and the lowest cost trip has been selected for each one of them.

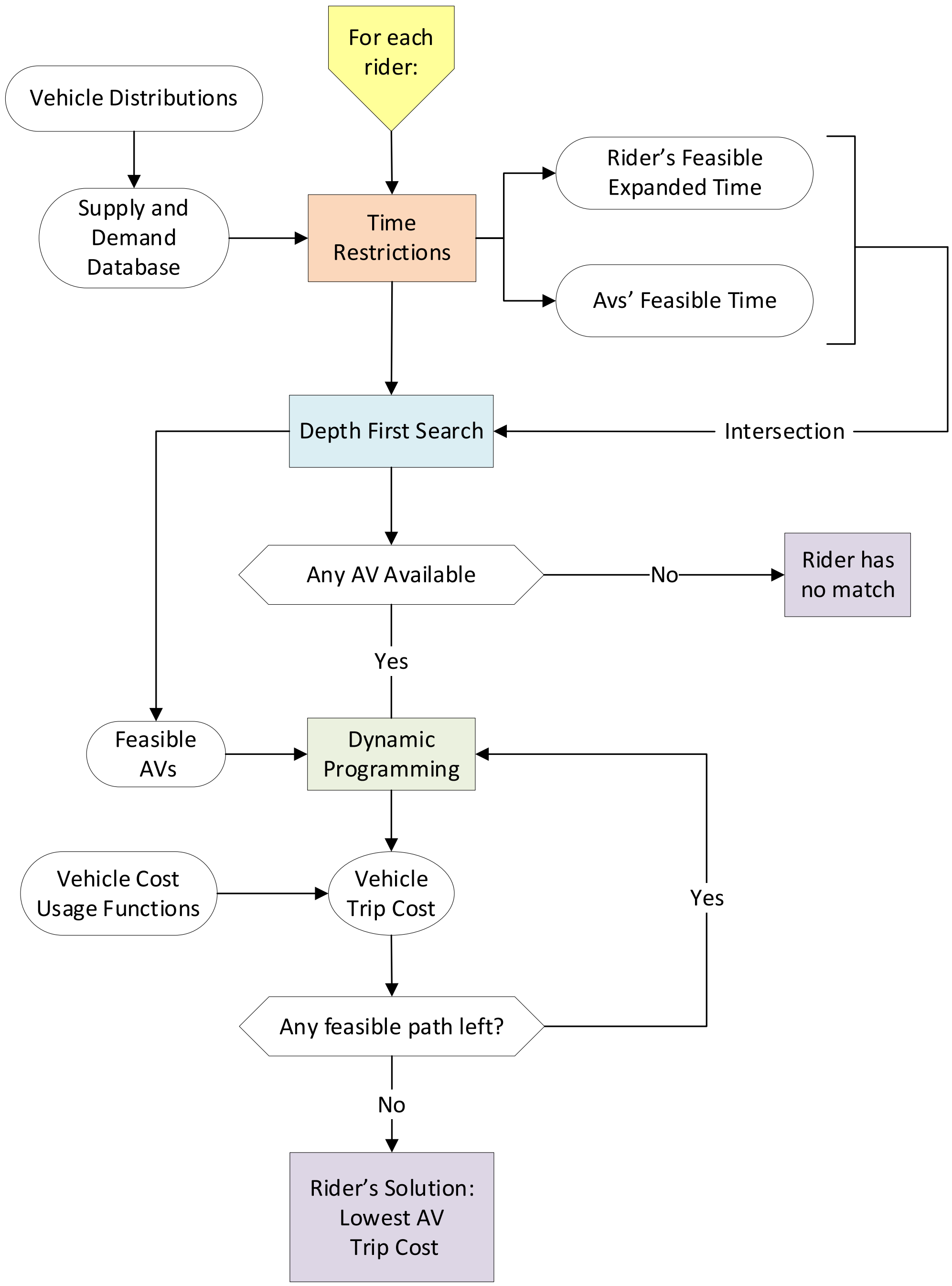

Figure 34. Ridematching solution algorithm flowchart for the AV sharing system

Agent-based modelling

Currently there is no available mathematical model that can analyze the new changes in the transportation scenarios considered in this dissertation, due to the complexities involved. In order to consider the increased usage of vehicles and how a new cost model could impact the decision making, we need to simulate different scenarios for these vehicles and a demand that could be useful for this system to observe these changes.

The life cost model for Autonomous vehicles is meant to consider the total cost of a vehicle during its lifetime. This is especially important in a new situation where SAVs will have a higher importance and could even be thought as a new mode of transportation by themselves in the form of fleets of SAVs, serving the demand of a city or an area. These fleets of SAVs would be similar to the fleet of vehicles of a carsharing company with the advantage that the number of vehicles can be much smaller and can be much better optimized. This optimization can bring other challenges already mentioned, such as the increase on the usage per vehicle and the consequent reduction of the life of it. Here we study a proper cost function meant to consider these changes.

Even if AVs are getting more and more importance, and it is clear that they will arrive in the coming years, there are many things of which we cannot be certain. Because of that, there is not a mathematical model that can analyze the changes in the transportation situation. So, in order to consider the increased usage of vehicles and how a new cost model could impact the decision making, we need to simulate different scenarios for these vehicles and a demand that could be useful for this system to observe these changes.

The tool selected for this purpose is an agent-based transportation simulation modelling platform called Polaris, developed by the Argonne National Laboratory (Auld et al., 2012, 2015). This type of simulation has the advantage that users and vehicles can be created as agents with their own characteristics and present individualized information to observe how their transportation patterns change depending on the scenario. Polaris can simulate large-scale networks and can support the evaluation of traffic operation programs, which means that we can include our optimization framework within a Polaris-based platform and see the changes in the system performance through simulations of selected urban contexts. It integrates transportation network and demand generation, it is an open-source program, and it also has specific tools for traffic flow simulation, geographic information system (GIS) tools, and result analysis tools (Auld et al. ,2012 and 2015).

The research team at UCI is currently developing an Agent-based simulation platform for modeling a comprehensive set of future mobility paradigms (rideshare, carshare, autonomous vehicles, micro-transit, etc.). An important element of the system is an ownership paradigm called "mobility portfolios," recently developed at UCI (An, 2019), which allocates each traveler in the system with a portfolio of mobility options with associated prices, which are then expended by the driver. Named "Autonomicity," the agent-based platform is currently being developed based on the network of Irvine, CA, generally bound by SR-55, I-5, SR-73, and the El Toro Y, with I-405 passing through. The network uses current demand levels for travel desires and includes activity generation capabilities that are based on the California Statewide Travel Demand Model.

At one end of the spectrum a portfolio may include just a personal vehicle, and at another end, time-share ownership or use of a variety of modes such as rideshare, SAVs and transit with allocated "hours of usage". In this dissertation, we attempt to analyze some of the elements of the future mobility with a restrictive mobility portfolio that includes more advanced vehicle cost considerations, to obtain better solutions for the transportation system. The first cases of the framework will be analyzed with different sizes of quadratic networks and a corresponding trip demand. In the last case, especially due to computational requirements, the framework will be assessed using the Irvine network.

The relationship between the agent-based modelling and the ridematching optimization includes feeding the Polaris simulation with the results of the mobility situations named as shared mobility modules: SAVs, micro transit and mobility portfolios. We can see (Figure 35) an example of the scheme of the optimization, with the decomposition of the subsystems. This algorithm relates to the Polaris simulation, and the results of one are used as inputs for the other. This means that the results of the simulation, including travel times, trajectories, characteristics of the network or of the vehicles, are used to optimize the itineraries in the ride-matching algorithm; and its results are the itineraries that serve as input for the agent-based simulation. At the same time, these results are used for the optimization of the subsystems and their own results are reported back to the ride-matching algorithm. We consider the implementation of the subsystems as a part of our optimization, to be used as inputs for the ride-matching algorithm, and not directly to Polaris.

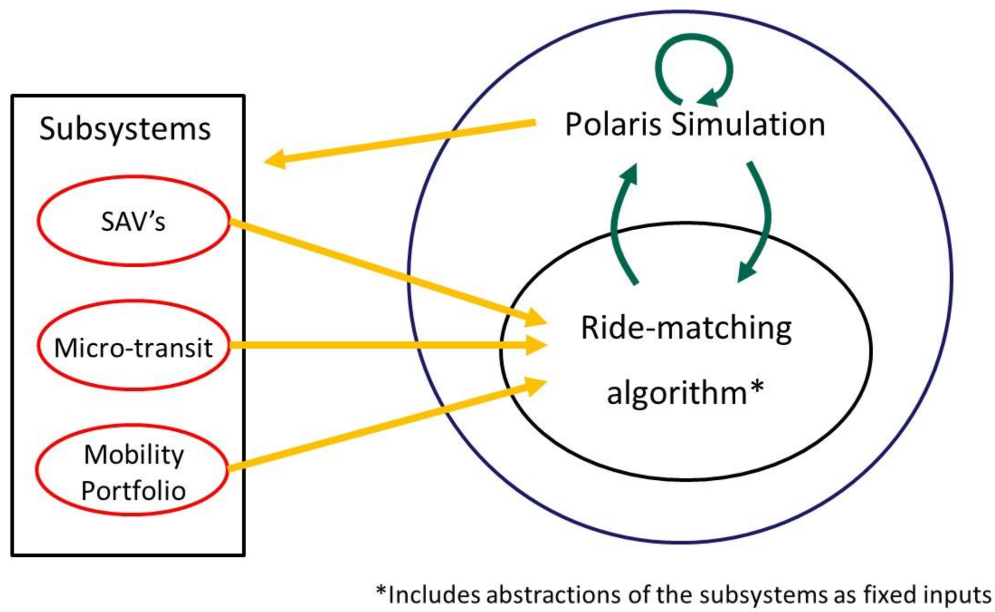

Figure 35. Proposed scheme of the optimization, including the Polaris agent-based simulation, ride-matching algorithm, the detailed subsystems, and connections

Vehicle update module

The next step of the framework consists in the data management of the results obtained from Polaris. This dissertation is based on the increased usage and costs of vehicles; thus, we would obtain the usage information of the vehicles on the system for each scenario and update the information that we already have. The initial information of the vehicle's usage would be based on distributions created from the information obtained from the NHTS survey described in chapter 2. Then, for each case, we initially build a dataset which includes that information and the related cost of the use of each type of vehicle as described in chapter 3. This information is used to obtain the best vehicle cost trip for each rider, and the results obtained are used to update this vehicle information.

The process of updating information includes keeping the cost and usage information of all the vehicles in the system, not only the ones currently used in each iteration of the framework, but also the ones that are not and might have been used in previous iterations or will be used in later iterations of the process. As the focus of this framework is on the mobility provider and its vehicles, we also created a bookkeeping system which stores for every vehicle the usage on each iteration and how the cost updates as the vehicle is being used. This information will be used in the following step where we analyze the benefit and cost impacts of the system.

System cost analysis

The last module of this framework is to analyze the interactions between the elements and the costs derived from the simulation. It allows us to optimize the system on a higher level based on the point of view of the ridesharing provider. We would consider a pricing scheme associated to the use of the vehicle from this system, and the benefits and costs associated to the user's mobility. We would analyze the fleet and scenarios that give better results, and the impact of using the vehicle trip cost usage function to obtain a better performing transportation system, which not only considers the increasing use of vehicles but also the costs associated to these new uses.

For any company a managing acting as a ridesharing service provider, we can analyze their profitability by subtracting the expenses in terms of costs derived from providing the mobility service, from their revenue obtained from riders using the system. The revenue is defined as the sum of all the income for providing the service. This can be linked to the mobility portfolio scenario where we can introduce the plan payments, where users pay certain amount to use the mobility service during a period of time with certain limitations on the number of hours for each mode. In this dissertation we focus on the increased use of vehicles, as such, we would work with a limited form of payment where riders pay for the service that they are getting (s_{a_y}).

$$R_a = \sum_Q S_q = \sum_Y s_{a_y}$$

From the revenue we can deduct the expenses that the company a incurs. These come in the form of costs derived from using the vehicles and travel time from the agents using the vehicles. Then we can obtain the profit for any company of the system, as below.

$$E_a = \sum_{V_a} f(miles\ v\ used) + \sum_Q f(travel\ time):$$

$$\sum_{V_a} f(miles) = \sum_{V_a} C_{v_a} \cdot Z_{v_a} = \sum_{V_a} v_a \cdot \left(c_{f_{v_{au}}} + c_{w_{v_{au}}}\right) \cdot z_{v_a} =$$

$$= \sum_T v_{a_{t_i}} \cdot \left(c_{f_{v_{atu}}} + c_{w_{v_{atu}}}\right) \cdot z_{v_{at}} = \sum_T \sum_{V_t} v_{a_{t_i}} \cdot \left(c_{f_{v_{atiu}}} + c_{w_{v_{atiu}}}\right) \cdot z_{v_{ati}}$$

$$= \sum_T \sum_X v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}}$$

$$\sum_Q f(travel\ time) = \sum_Q q \cdot D_q \cdot H_q = \sum_Y y \cdot d_y \cdot m_y \cdot h_y$$

$$E_a = \sum_T \left(\sum_X v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}} + \sum_Y y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}} \right)$$

To these expenses, in our ridesharing system we would also consider the extra costs for the riders that are part of the shared mobility system but could not be served β, and in the case of the autonomous vehicles, the costs for the extra AVs not being used γ. β reflects the costs for riders having to use their personal vehicles as a mode of transportation and it would be obtained from the Polaris simulation. With the mileage and the travel time, we can obtain the cost for using their vehicle in a similar way that we obtain the cost of using the vehicles from the ridesharing provider. In the case of γ, we can have different approaches of the cost incurred of owning a vehicle that will not be used. Several costs can be considered in this case, like the parking or depreciation. In this situation, we would consider the equivalent usage that each vehicle should have, and we can obtain it from the proportional usage of the average value of fifteen thousand miles per year times the iteration simulation time, which we will note ask.

$$\beta = \sum_{Y_n} \sum_{T} \left(\left(v_{ty} \cdot \left(c_{f_{v_{tyu}}} + c_{w_{v_{txu}}} \right) \cdot z_{v_{tx}} \right) + \left(y \cdot d_y \cdot m_y \cdot h_{y_t} \right) \right)$$

$$\gamma = \sum_{V_a} f(travel\ time\ v\ not\ used) = \sum_{V_a} C_{v_a} \cdot k = \sum_{V_a - G} v_a \cdot c_{v_{ak}} \cdot k$$

$$B_a = R_a - E_a =$$

$$= \sum_{Y} s_{a_y} - \left(\sum_{T} \sum_{X} v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}} \right) \cdot z_{v_{atx}} + \sum_{Y} y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}} + \beta + \gamma \right)$$

In order to calculate the revenue of the company we consider a pricing scheme where we have a parameter that weights the costs of using the service and increases revenue accordingly. This parameter is formulated as α and will be considered a profit parameter, and could be assign for each company a. We would formulate the characteristics of the pricing scheme for any service provider a, and to simplify the formulation and without losing generality, we would refer to this profit parameter as α instead of α_a. As a result, we would have the pricing p_{a_y} as the profit parameter times the cost for each rider for using the service of the company.

$$p_{a_{y\ (y\in Yd)}} = \alpha \cdot (\left(v_{a_{t_y}} \cdot \left(c_{f_{v_{atu}}} + c_{w_{v_{atu}}}\right) \cdot z_{v_{aty}}\right) + d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}})$$

We have studied several ways to introduce this parameter. It could be included as a constant that not only depends on the company offering the system, but also on the vehicle type used, and also as a two variable which would depend on the mileage used and the travel time of the vehicle.

One variable depending on the vehicle type used α_t:

$$P_a = \sum_Y p_{a_y} = \alpha_t \cdot \left(\sum_T \sum_X v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}} + \sum_Y y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}}\right)$$

Two variables depending on use and time and the vehicle type:

$$\alpha_{1_t}: factor\ for\ vehicle\ usage\ cost\ type$$

$$\alpha_{2_t}: factor\ for\ travel\ time\ cost\ type$$

$$P_a = \sum_Y p_{a_y} = \left(\sum_T \sum_X \alpha_{1_t} \cdot v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}}\right)$$
$$+ \left(\sum_Y \alpha_{2_t} \cdot y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}}\right)$$

As a result, if we consider the pricing of all the users of the transportation system, we can obtain the total revenue, and with the costs, the profit of the service provider. This system analysis forms part of our framework as it would be used to analyze the system and optimize the mobility scenarios.

$$R_a = P_a$$

$$R_a = \sum_{Y} s_{a_y} = \sum_{T} \sum_{X} \alpha_{1_t} \cdot v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}} + \sum_{Y} \alpha_{2_t} \cdot y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}}$$

$$B_a = R_a - E_a =$$

$$\left(\sum_{T} \sum_{X} \alpha_{1_t} \cdot v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}}\right) + \left(\sum_{Y} \alpha_{2_t} \cdot y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}}\right) -$$

$$\sum_{T} \left(\sum_{X} v_{a_{t_i}} \cdot \left(c_{f_{v_{atxu}}} + c_{w_{v_{atxu}}}\right) \cdot z_{v_{atx}} + \sum_{Y} y \cdot d_{a_y} \cdot m_{a_{y_t}} \cdot h_{a_{y_t}} + \beta + \gamma\right)$$

Considering a profit parameter can increase the problematic of the framework. Moreover, it would be necessary to add a relationship between the people using the service and α because otherwise, service providers could increase systematically this variable to increments the profit of the system. To analyze the interaction between the elements of the system and the benefit-cost results from the system, we would consider in our case studies a scenario where $\alpha_{1_t} = \alpha_{2_t} = \alpha$, and a linear approximation between α and the number of riders of the system. Using the information from uber pricing and surcharge, we consider profit parameter to be bounded between 0 and 3. For values of $\alpha = 0$, the trips would be free, so every possible person would like to be part of the riders in the ridesharing system; and at

$\alpha = 3$, none of the users would be interested in being a rider, and all the agents would only be interested in being drivers of the system.

The framework presented is designed as a modular system where some aspects of it can be adjusted depending on the situation and the conditions of the network to simulate. One of the key aspects is the decision making of choosing to be part of the system or not, and once we consider a group of agents to be part of it, how we can determine who are considered as drivers or riders of the system. Riders have a more active role, where they are matched with drivers to make their trip. On the other hand, drivers have a passive role, where they have their trips and are waiting to be matched with any of the riders to serve them for their trip.

In this situation, agents will choose to use the service at a certain level of pricing on their trip. Then, for each alpha we can obtain the number of potential riders by considering the number of agents in the system. Different types of approximations can be presented in this scenario; however, the linear relationship allows us to better study and understand the interactions between the rest of the elements. The ridership results obtained would not be very different than the ones from a more complex relationship, and ultimately, we would need to generate a behavioral model than considers the personal transportation utility modes of users depending on pricing.

Including all the behavioral elements that can affect the individual utility of each agent can be very complex, will require a lot of data and that would also need to be adjusted with real information as the system is working. It would generate a disaggregate demand level where we would have individual information which would come from Big Data personal data. While these are realistic aspects, their consideration is deemed beyond the scope of this dissertation. For this reason, in order to simplify the process, we decided to simulate the network using our framework with aggregate-level demand data, while keeping the possibility of including more complex modules later. Understanding the importance of the behavioral component on this framework would still be important, thus, some of the behavioral considerations and implications of the pricing and the framework in general will be further analyzed in following chapters of this dissertation.

Discussion

In this chapter we have presented the key aspect of this dissertation which is the framework created to analyze new shared mobility systems based on the increase vehicle usage cost. We have introduced and analyzed all the agents and elements from the framework, the information it will use, the ridematching and simulation processes, and the mathematical formulation to optimize the system and analyze the results obtained. This framework is prepared to consider many different scenarios and costs, in particular situations derived from a shared mobility provider that matches users from the system, and the use of an autonomous vehicles fleet system.

We have also presented extra costs derived from riders wanting to use the system but not being able to be matched to another driver, or in the case of AVs, similar situations where there are not enough vehicles to serve the whole demand. Moreover, a pricing scheme has been presented, along with the interaction elements that would be considered in the next chapter. This process can be linked to the mobility portfolio cases where we restrict the used modes and their pricing subscription plans, with an improved emphasis on the use of vehicles, and how their impact affects the rest of the elements on the network.

We have considered the results found from the data analysis from the NHTS, which will be implemented in the case studies; and what we found were the most important costs. However, we have also noticed that this framework could be used to implement better policy scenarios and consider other costs related to vehicle pollution, for which we would only need a proper emission model associated with each vehicle type. These scenarios would not be part of this dissertation, but could be easily implemented with this framework, thus, would be considered for future work in this situation.

In the next section of this dissertation, we would present the interaction obtained between the elements of the framework in different scenarios, and the impact of considering the profit of the company as one of the most important variables. We would also comment how can we consider different fleet sizes and profit parameters, in order to obtain the most profitable situations from the point of view of the vehicles and the service providers.

CHAPTER 5:
Vehicle Cost Framework Case Studies for Ridesharing Systems

Introduction

In the previous chapters we have described all the tools necessary and useful for the purpose of this research. Here we present several case studies which incorporates all of them and attempt to generate a model combining new shared mobility systems. In each scenario, we will apply the framework presented and generate a situation in which the vehicles involved are matched and optimized according with their vehicle trip cost, which is obtained from their vehicle usage cost function.

The vehicles' characteristics will be generated and adjusted considering the distributions obtained from the NHTS 2017 and described in chapter 2. The objective is to include the heterogeneity described in the vehicle cost usage functions. Furthermore, the increase on information of the users and the rise of Big Data expands the possibilities of this type of model by having full information about the system. Knowing all the characteristics of the vehicles and the travel patterns of the people, makes it possible to assess the diverse demand of the system with different configurations modeled for the fleet of SAVs.

The simplest form of applying the vehicle cost trip framework is a limited mobility portfolio where three discretized travel statuses: shared- ride drivers, shared-ride riders, and solo-driver options. In this section we perform case studies on test networks and finally on a real network (Irvine), and we confirm that the proposed framework improves system performance by generating incentives for people to use shared mobility options

Case Study 1: Cost-Usage Equilibration

The first case study of the vehicle Cost Usage Framework consist of a sequential process of ridematching users in a network to equilibrate the cost and usage of vehicles. Several scenarios are presented, including an initial situation with no ridematching, and a first scenario where the cost of vehicles does not interact with the framework. These are base situations. Then we add new situations where the cost of the vehicles affects the ridesharing system and the whole framework is applied and modified to create a sequential process. The objective is to observe the increase in the usage of vehicles as ridesharing systems are included, and how vehicle cost usage strategies can improve the mobility system as it is being used.

We have created a 4-by-4 node symmetrical network that can be used as an example for future zones of bigger networks (Figure 36), with 16 nodes (blue) and 24 links (green). All internal nodes are considered as a traffic analysis zone (TAZ) which can generate traffic demand. Then, we consider an initial demand of 2000 agents with their origin and destination (O.D.) randomly assigned. From the total trips, we obtain from the NHTS 2017 survey that about 12% correspond to working trips, which gives us about 240 agents; and from those we select 15 which could be interested in changing vehicle or thinking about initially adopting the ridesharing system, and not buying a new one.

To analyze the impact of the cost function we proposed a ridesharing system, we set a peer-to-peer ridesharing scenario and divided people into two groups: (a) shared- ride drivers (i.e., who is willing to share empty seats in his/her vehicle while traveling) and (b) shared-ride riders (i.e., who is willing to use their own car or travel on others' car empty seats). We randomly select 10 and 5 people as a ridesharing driver and a ridesharing rider, respectively, and the rest of unselected people travel the network with their own vehicle. Both groups, the people that do not participate in the ridesharing system and the drivers not matched with any riders would be part of the solo-drivers.

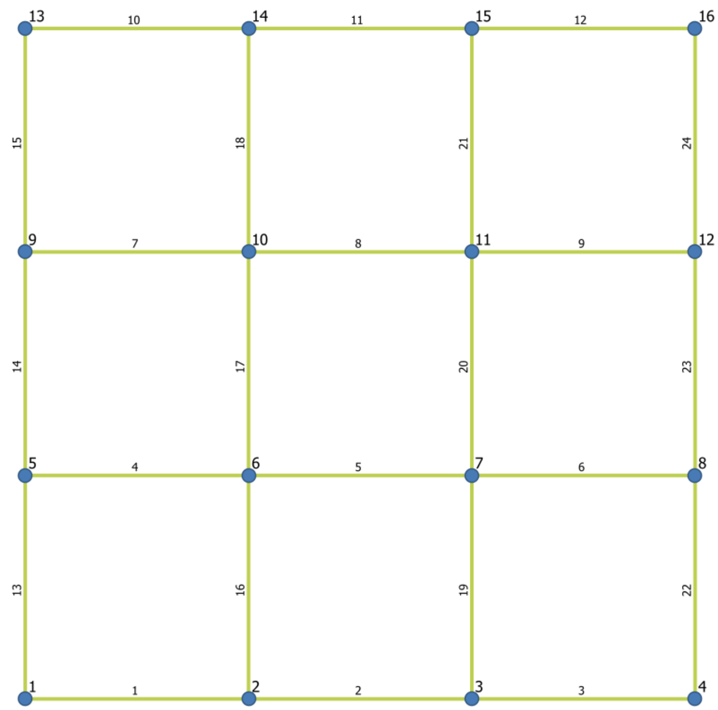

Figure 36. Quadratic 4 by 4 test network with node and link enumeration.

Given the information of the NHTS, this study introduces four different types of vehicles – such as conventional vehicle (car), Sport Utility Vehicle (SUV), pickup and van, which will be the same vehicle types considered in the rest of the case studies. Using the cost function and the variables considered, we provide a cost for each vehicle type per mile. We also set each individual's vehicle type randomly and we conduct the ridesharing scenario. In this study, travel times are assumed not to be affected by the performance of the shared mobility system, as it is still fairly small in the network. Travel times are used but we are not looking at those changes, for ride matching we consider static travel times on the links. We present illustrated studies from an idealized case, where we want to show the interactive effects between pricing and ridesharing, when a proper optimal ride matching algorithm is used.

Vehicle cost – system interaction

In the simulation we consider scenarios with and without ride matching, comparing for those 15 potential agents for our system the total vehicle miles travelled (VMT) and the cost of the vehicles (TC). In the first step we assume a scenario 0 with no ride matching, where we expect the lowest VMT and cost, at the expense of the highest number of vehicles on the system, due to the people having the most optimized trips with their own vehicle only from their origin to their destination. Then we consider other scenarios with our 10 drivers and 5 riders, where due to the ride matching and the route adjusting for pick up and drop offs, we will have increased VMT and TC. We analyze situations where the matching between drivers and riders is done in the regular way, assuming no difference between vehicle types (scenario 1) or trying to optimize the system by assigning the vehicle with the lowest cost for each rider's trip (scenario 2). We will start by using the average cost for each vehicle type, assuming the cost function generated over a period of 200,000 miles of lifetime cycle.

We find that in both scenarios all riders are served, and all the trips are completed (Table 2). Only the results derived from the ridesharing system are presented from the whole group considered. As expected, the initial scenario with no ridesharing has the lowest VMT and cost of vehicles. Then, we observe that for both scenarios with ridesharing, there is an increase of the total mileage, which reinforces the idea presented of including a system based on the mileage of the vehicles. We expect that this value of VMT would be reduced as we scale the size of the network and the impact of detouring in the drivers is reduced.

Table 2. Case study details and results

Vehicle Costs ($ per mile)	Car	0.47
	Van	0.60
	SUV	0.58
	Pickup	0.68
VOT ($ per hour)	Driver	10.00
	Rider	5.00
Mileage (VMT)	Scenario 0	34.80
	Scenario 1	45.98
	Scenario 2	44.74
Travel Time (VHT)	Scenario 0	0.81
	Scenario 1	1.21
	Scenario 2	1.17
% Ridesharing Travel Time from VHT	Scenario 0	0.00
	Scenario 1	39.71
	Scenario 2	41.06
Drivers matched (%)	Scenario 0	0.00
	Scenario 1	60.00
	Scenario 2	60.00
Cost of trips ($)	Scenario 0	26.71
	Scenario 1	37.90
	Scenario 2	36.24

We observe that the second scenario, which assigns the vehicles from drivers to riders based on the cost depending on the vehicles, reduces the total cost of the vehicles while maintaining a similar level of VMT, and increases the time vehicles are shared. This means that only by making this small consideration we would be able to reduce the cost of the system, and even further if we applied more specific cost functions. Ridesharing increases the cost of the system in terms of VMT and VHT (vehicle hours travelled), with the benefit of reducing the total number of cars, not only on the road but in every aspect. This represents a substantial benefit for the system, which reduces their total cost and impact.

In the final step we run the same scenarios several iterations, extrapolating the vehicle mileage results, to analyze the impacts of the increase ridesharing in the vehicles, and the use that we would need up until one vehicle reaches its life mileage (considered to be around 200,000 miles) and would need to be replaced. In particular we will compare the scenarios in which we reflect the effect of ridesharing, considering that all the vehicles start with zero miles, and will start accumulating as they are used.

Moreover, this allows us to run a special case of the scenario 2 (scenario 3), in which we can adjust the cost of the vehicles at these steps and rerun the ride matching algorithm. This process is developed in a sequential approach, where one part of the framework is being repeated (Figure 37).

In this scenario 3, we run the same ride matching algorithm assuming all the vehicles start from a situation with a zero mileage associated and with the corresponding cost associated to that mileage, instead of using no cost or an average cost per type. Then, we get the results of how they are matched and the characteristics of their trips, and we extrapolate the results assuming the same level of use. With new values of mileage, we can update the cost per mile of vehicles, and rerun the ride matching algorithm, obtaining new matches that can be simulated again. We will do this process until a vehicle reaches its life mileage, assumed at 200,000 miles. Finally, the system cost analysis is performed to compare the different scenarios. These effects have particularly importance in this last case, where we could start to simulate a subscription service company with a set of vehicles used for ridesharing, which will want to optimize the cost of the vehicles and their weathering and might intent on mimicking a similar process on updating vehicle costs.

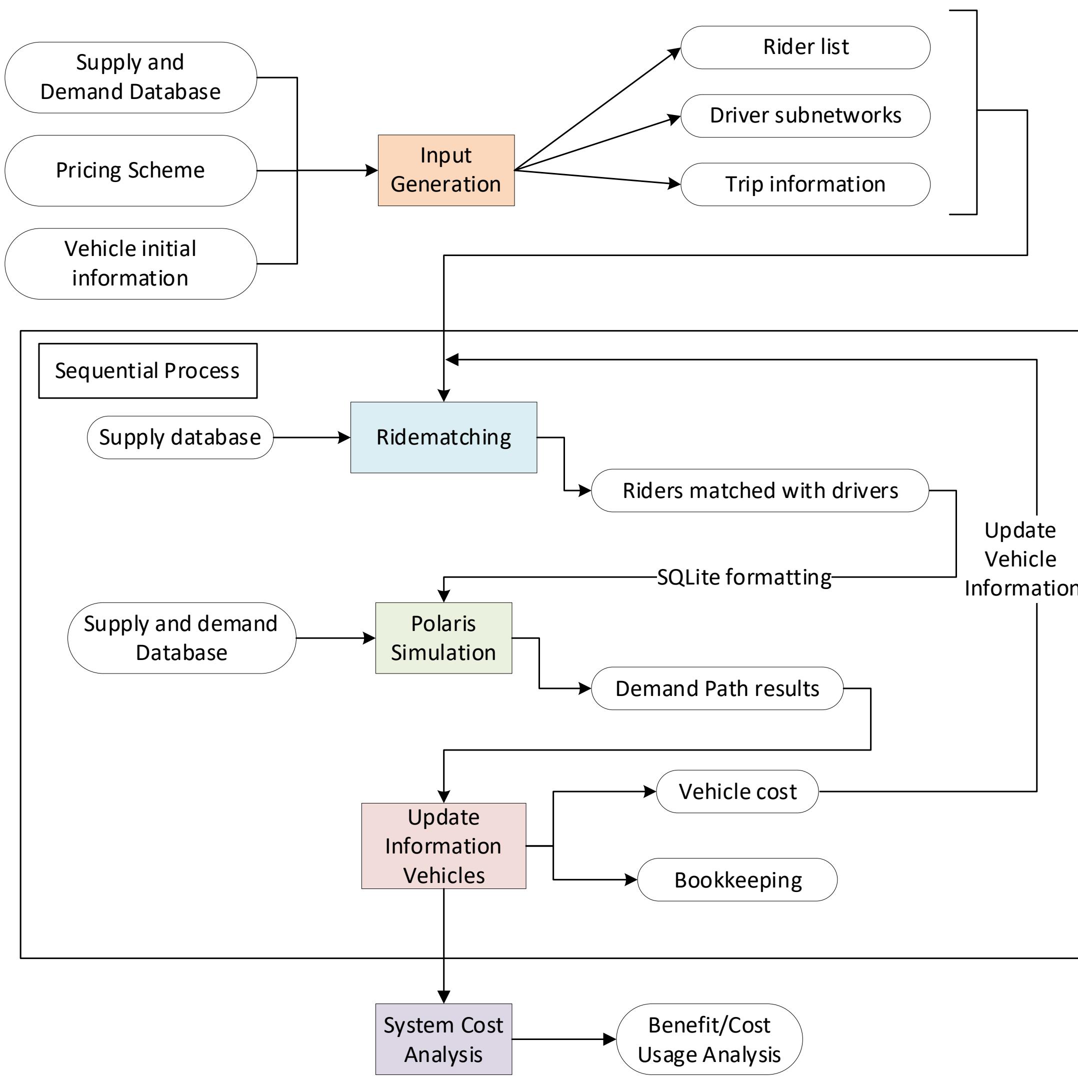

Figure 37. Vehicle cost usage framework diagram for sequential cost-usage equilibration

We observe how the scenario 1 is the first one to have a vehicle with 200 thousand miles, as it did not optimize the cost of the vehicles depending on their type, nor adjusted as they were used. Then, in the scenario 2, we are able to increase the number of iterations by 25% only by making sure that we consider at least an average cost. Then we run the scenario 3, where we observe a possible increase in iterations of more than 50% compared with scenario 1 and more than 20% with scenario 2. Not only we are able to extend and average the miles we put on the vehicles of the ridesharing system, but also, we reduce the cost of the system at every iteration and within time.

If we compare the cost of the trips applying the formulation presented in chapter 4 and the information obtained from Polaris, we observe a total cost reduction of 11% between scenarios 1 and 3, and a reduction of 5% between scenarios 2 and 3. If we pay attention to the differences in the cost for each iteration, initially the costs are the same, as we still consider the lowest trip cost for each user, but as the vehicle information is updated, the differences increase (Figure 38). At the last iterations, the differences between the iteration costs are 16% between scenarios 1 and 3, and a reduction of 9% between scenarios 2 and 3. We can also observe how the shape of the three curves is very similar due to the calculation using the same vehicle type distribution and vehicle usage cost function.

The promising results show the importance of these studies as we start to consider the effect of new types of shared mobility systems. The more the vehicles are used, the more impacts that we see as we introduce vehicle cost usage functions in the transportation framework. As we focus more on these aspects, other elements like the rate of vehicle cost updating, the pricing scheme, and the costs of riders not being served and vehicles not being used, impacts the sustainability of the system from a service provider point of view.

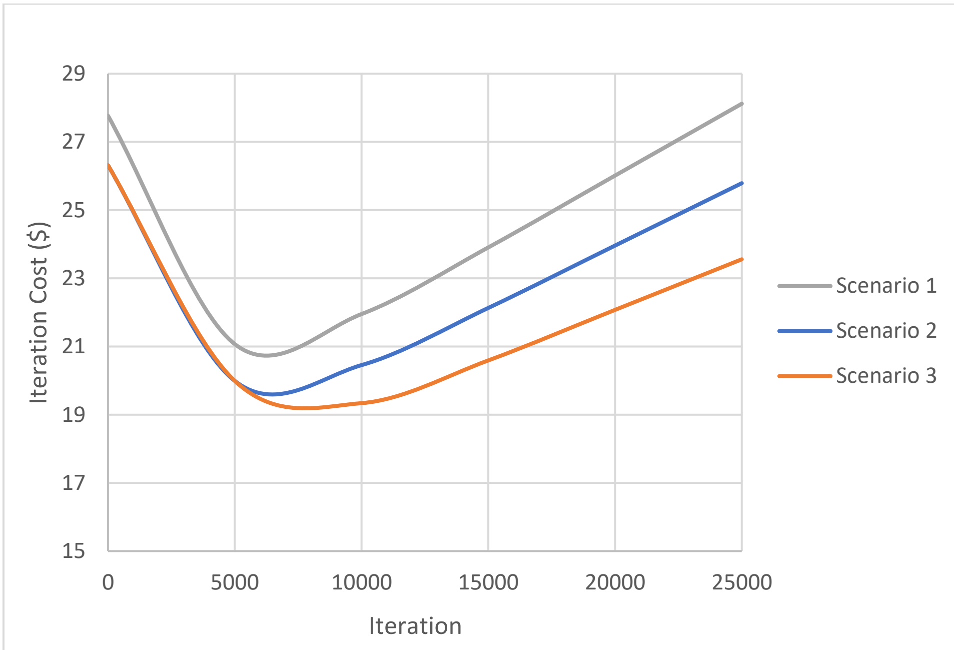

Figure 38. Total trip cost iteration comparison between scenarios 1, 2 and 3

Case Study 2: Iterative Process for Optimal Pricing

The second case study of the Vehicle Cost Usage Framework consist of an iterative process for optimal pricing of ridematching users in a network. In the first scenario we analyzed the impact of including a ridesharing system, with and without vehicle types and updating vehicle costs. Now, we include a pricing scheme which, as previously described, would control the profit of the service provider. We test the framework by considering individual scenarios depending on the profit parameter. The objective is to determine the optimal pricing depending on the objective of our service, such as the maximum profit, the number of agents participating, the riders being served, or the minimum cost.

In this case study we consider different network and corresponding demand sizes. We analyze the best profit parameter in a 10 by 10 network with 100 trips (Figure 39), a 7 by 7 network with 45 trips and a 4 by 4 network with 15 trips. The number of trips corresponding to each network are obtained from the initial hypothesis presented in the first case, and then escalated for each bigger network size. Following the formulation presented, the number of riders and the proportion with the drivers of the system for each case is obtained as an aggregate demand from the pricing scheme and the profit parameter. Similar to the previous case, we consider the distributions of the four vehicle types described in case one. Moreover, we also consider the extra costs β, and the value of γ (autonomous vehicles not being used) as zero. Finally, as we are not considering the total usage of the vehicles, besides the vehicle type information we give them an initial odometer mileage value obtained from the vehicle distributions from the NHTS described in chapter 2.

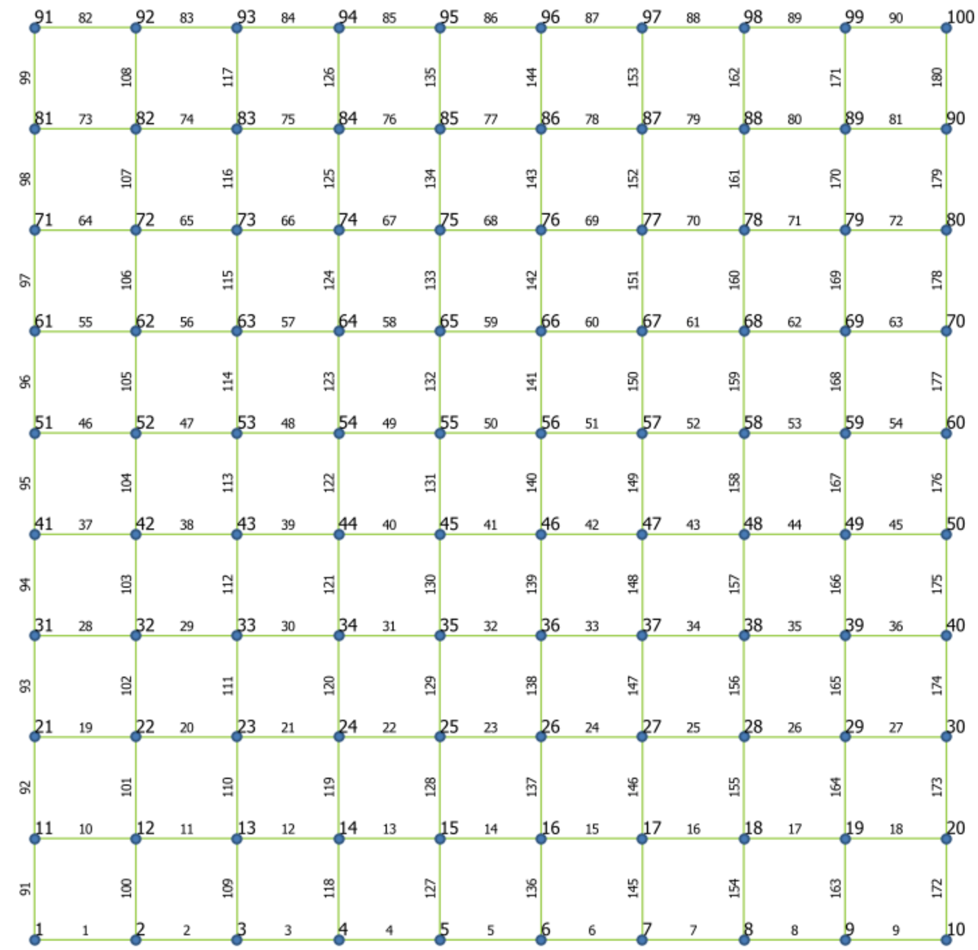

Figure 39. Quadratic 10 by 10 test network with node and link enumeration

For each situation the framework is applied. Profit is the comparative variable, which will depend on the profit parameter and the proportion of drivers and riders. In this case study, the riders are chosen randomly from the demand database trip information, which adds a degree of freedom that increases the variability of the profit results for each iteration. Not only the riders, but also the drivers and their trips control who they can ride with and the trips that they can make. Both agents are also affected by a flexibility parameter that controls how much can they be detoured and would also have an impact on the variability of the results.

For this reason, this case study is presented as an iterative process of stochastic repetitions. Profit is the comparative variable between scenarios, which consists of the application of the framework for each network and for each value in the range of the profit parameter. The results obtained will be repeated and averaged changing the selection of riders with the use of the seed function from our Python-integrated framework code. The adjusted diagram of the framework includes a looping section where the seed is updated after the simulation (Figure 40).

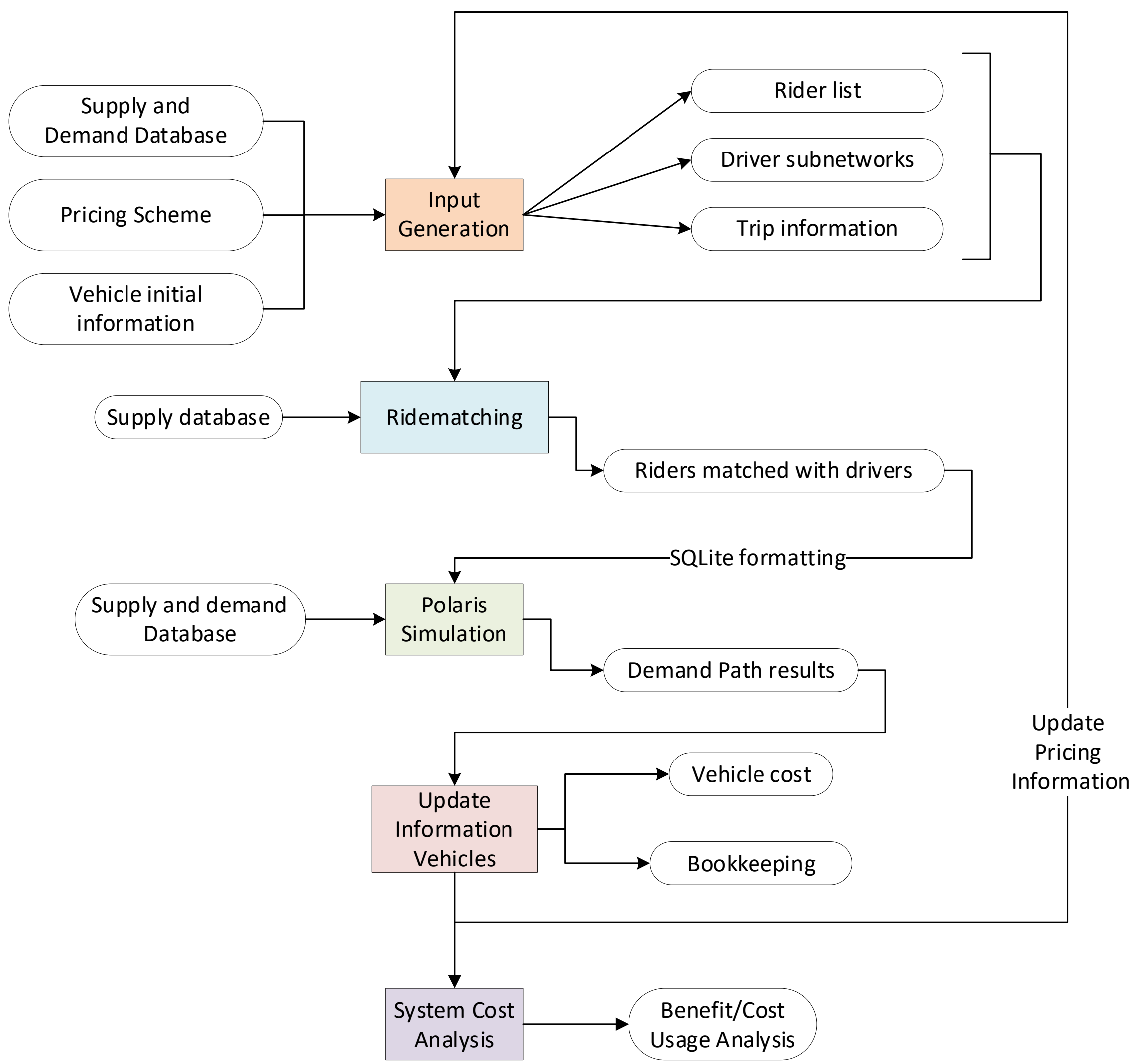

Figure 40. Vehicle cost usage framework diagram for iterative optimal pricing

The simulation results are analyzed and stored for each simulation. Then they are averaged and analyzed in the system cost analysis block. However, the question at this point is how many iterations do we need until the average value obtained is representative of the simulation results? For this purpose, we make use of Iteration Variance Reduction schemes, which will be further examined in the following section.

Iteration variance reduction

In each scenario, the results of each run can be affected by the riders selected, the drivers, the network, and the characteristics of their trips. This may represent a problem where even with the same number of similar riders, running the algorithm can return very different results. Also, adding or removing a rider can affect the whole network because of the implications of their trip and the consequent selection and removal of a possible driver.

We are interested in observing a set of possible solutions for the same situation. Each result or solution consists in the information of the system after tunning the ridesharing simulation with the corresponding cost and the ratio of riders and drivers. Then we can compare and collect the results obtained and use the average performance to summarize the model with every alpha considered. This raises the question as to how many repetitions are enough to sufficiently characterize the skill of this simulation algorithm. It is often recommended to use 30 or more repetitions. We use common statistical methods to estimate a right number of repetitions to effectively characterize the performance of our algorithm (Kahn and Marshall, 1953). This process can be followed using our three test networks (4x4, 7x7 and 10x10), and also compare the impact of the size and differences that can appear by considering smaller networks.

We use the seed function to seed the random number generator to ensure that we always get the same results each time the code is run with the same seed. We run each scenario 20 times with a different seed number, and then, we study the results with basic statistical analysis tools and analyze the impact of the number of repetitions. Given the nature of the data and the impact of considering an aggregate demand level, we are focused on obtaining an average value which can be used as a representation of the simulation (Hanck et al., 2021). However, we are also aware of the implications on the deviation of the results, and more comments will be given on the dispersion of the results obtained for each alpha case and network combination.

We can get an idea by plotting the number of repetitions of an experiment against the average of the results from those repetitions. We would expect that as the number of repetitions of the experiment increases, the average obtained would quickly stabilize. As a result, it should produce a plot that is initially noisy with a tail of stability.

If we analyze the plots for each network, we can observe that there are some differences in the shapes of the curves for each profit parameter, but they follow a similar pattern corresponding to the one described. These curves are a bit noisy at the beginning but after six or seven iterations they get some stability around the final average of the profit of the simulation (Figure 41 for the 10 by 10 network, Figure 42 for the 7 by 7 network, and Figure 43 for the 4 by 4 network, where each color for each curves represents a different profit parameter value).

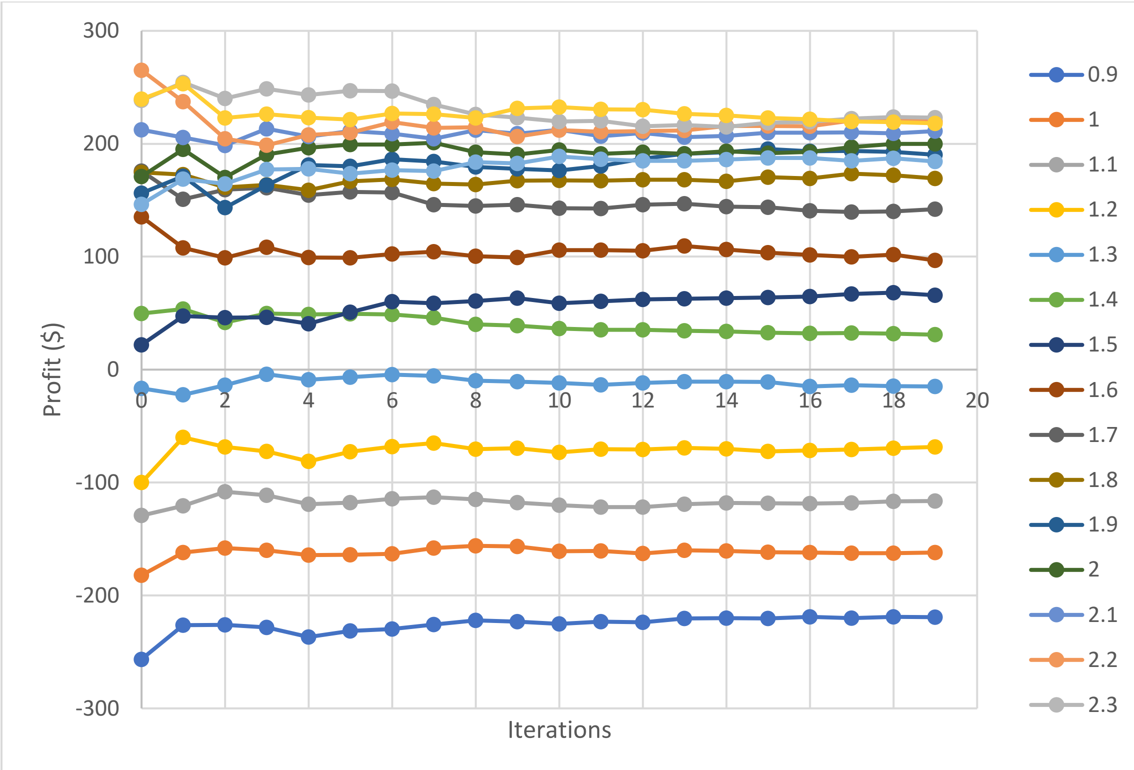

Figure 41. Profit distribution of the 10 by 10 network iterative process

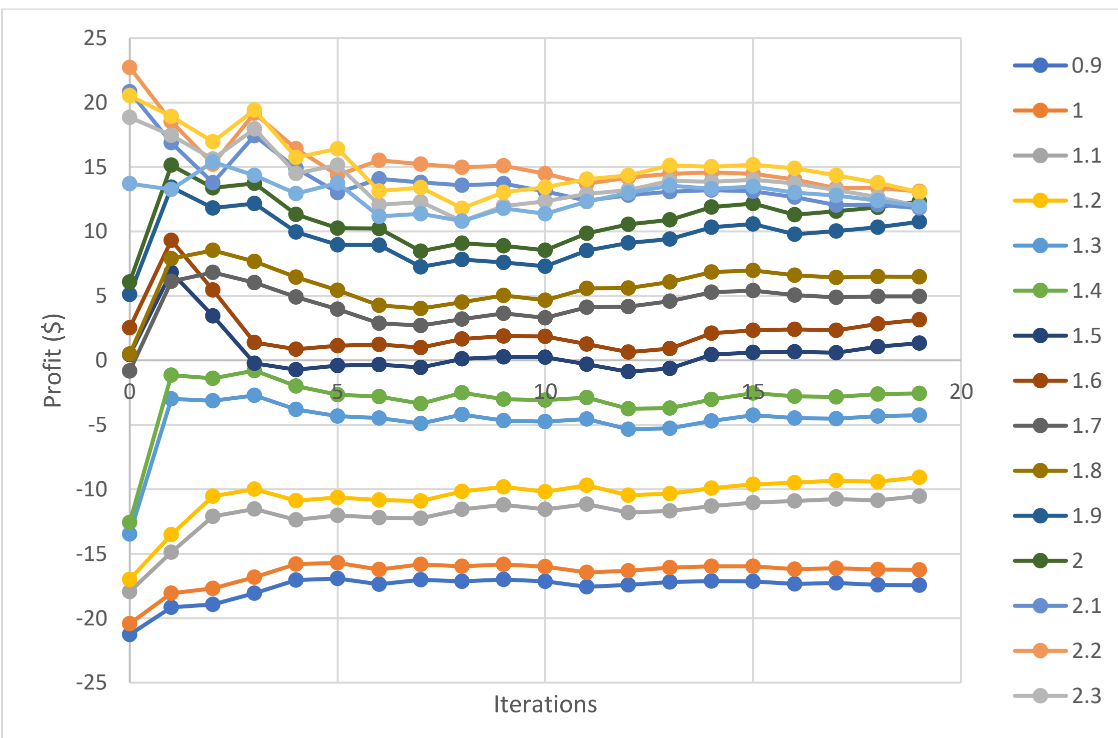

Figure 42 Profit distribution of the 7 by 7 network iterative process

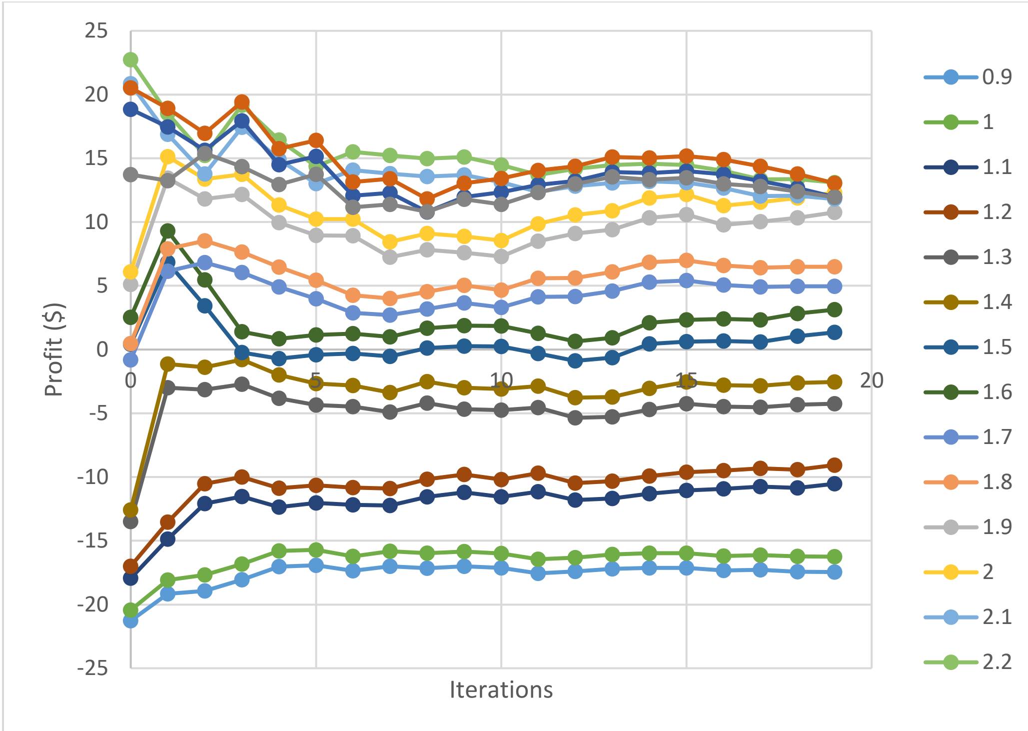

Figure 43. Profit distribution of the 4 by 4 network iterative process

The averages can be positive or negative depending on the results obtained from the value of alpha; and even some situations where some iterations give positive or negative results for the same alpha. From this analysis we can conclude that it might be useful to use this number of iterations to not overextend our iterations. For this reason, and to be on the safe side of our simulations, we selected 10 as our number of iterations.

It is also very important no notice that as the network gets bigger, the results also appear to be smoother. Specifically in the case of the four by four network, there seem to be some simulations from where the results obtained differ a lot from the average. This might be the direct result of the network's being smaller itself. In particular, a smaller number of agents and a smaller number of combinations of origins and destinations can bring this situation. When there is a small change in the system, in the case of the smaller networks it can change a lot the scenario. Not choosing the correct agents or changing a rider for a driver can mean that nobody is able to pick some other rider. This concludes in situations with higher benefits or higher costs for similar scenarios, and a higher deviation in the average profit.

Iterative process results

We have observed that the results among the three networks are very similar in terms of shapes and distributions. Thus, the results obtained would be scalable between those network sizes and even with bigger ones. As the results obtained from the 10 by 10 network show smoother representations, next we will explain them in more detail, assuming a similar behavior in the other smaller networks, and with after a ten iteration average process.

The most important initial result is the interaction between the profit of the ridesharing system as a function of the profit parameter alpha (Figure 44). The curve obtained is always negative for values of alpha smaller than one. The reason behind is that alpha is a coefficient of the pricing which gets the cost of the riders by multiplying the cost of the rideshared trip times alpha. A value of alpha lower than one would mean that the riders would be paying less than what the trip costs (without even considering extra costs), thus, negative profit. We would only consider these situations when the ridesharing system would be subsidized, because otherwise, the service provider would be working with losses.

Due to the interaction of riders and drivers, extra costs are generated which reduce the profit and displace the value of alpha to a number around 1.3-1.4. From there, the profit curve follows an almost symmetrical shape, with a maximum profit around the value of 2.3. Initially the are too many people wanting to travel and just a few drivers, and at that point, the number of riders who can share a ride is optimal.

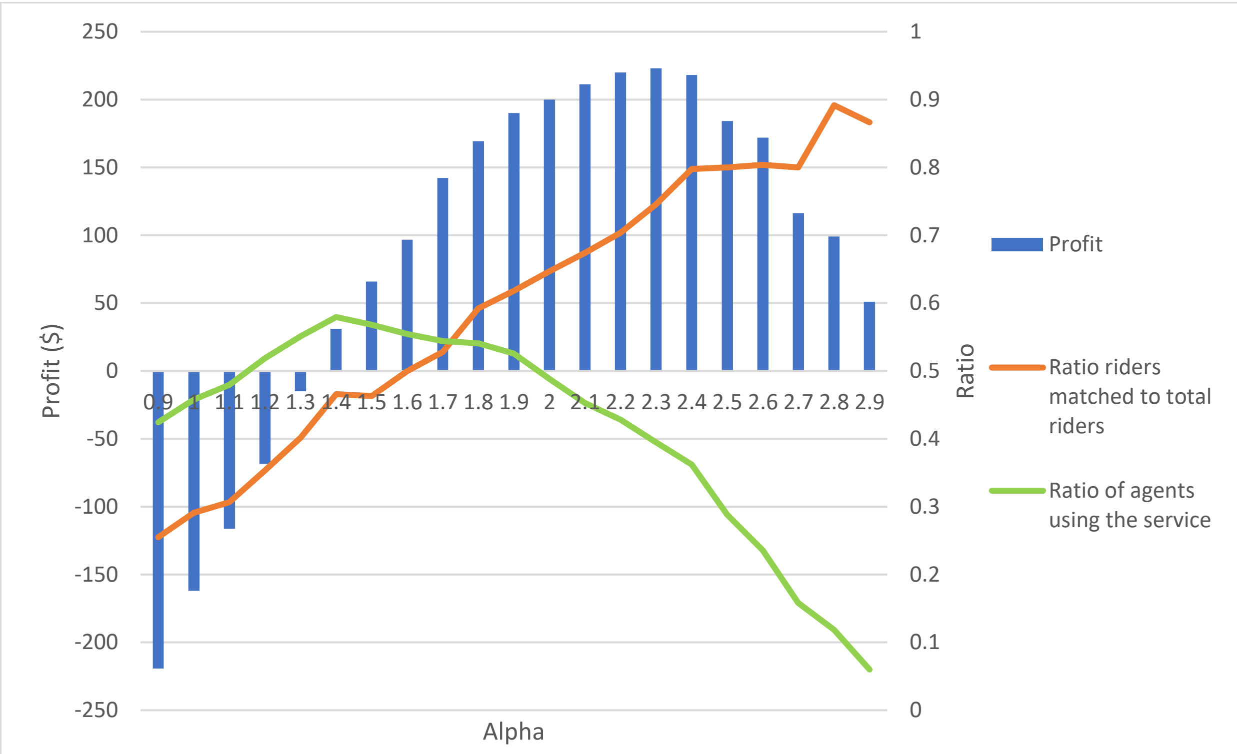

Figure 44. Profit distribution as a function of the profit parameter

We can also analyze the interaction between the profit parameter and the number of agents being matched in the system, especially compared with the ones that wanted to be part of it initially, but who may or may not be matched (Figure 45). We can see how the ratio of riders matched to drivers matched is a slightly increasing curve that gets closer to one. It is lower than one because given the ridematching algorithm, it would be easier to have more drivers for one rider, than a driver taking two riders. As alpha increases so does the number of drivers and reduces the number of riders. Thus, we have less riders, and the possibility of having multiple drivers serving trips is also reduced. In other type of bigger networks where we might have more drivers, the possibilities of having trips that match better the ones from the riders would be higher, and there would be a competing effect on the potential drivers and the transfers. In that case, competing effects of transfers and extra costs would be important, but not in this situation.

Similarly as above, we have the opposite ratio which indicates how many drivers are assigned per rider on average. This number would be even bigger as we consider repeated drivers, however, for smaller networks this effect would not affect significatively the ratio. We observe higher ratios at the beginning, where we have just a few drivers that would offer their ride to a big number of riders. As the number of riders is reduced, there are less possibilities of match with the drivers.

The proportion of riders to drivers is very important to determine how many of them will get matched. For each value of the profit parameter, we have a different ratio with a shape that follows a shape similar to a negative exponential. If we consider the ratio of riders matched to the initial number of available drivers, we can see a decreasing trend that ends up following the riders to drivers' proportion. As we increase alpha, we have more drivers and less riders. The number of riders matched initially increases as we have more drivers available, however, considering the ratio of riders matched and drivers matched having a negative slope, with higher alphas there are more drivers matched than riders matched. Thus, even if the number of riders matched increases, the number of drivers matched increases even more, and so does the number of drivers. As a result, we have a negative slope for this ratio, though a bit less negative than the ratio between drivers and riders.

As the profit parameter increases, there are less riders and more drivers, and as a result, each rider has more possibilities of finding a suitable driver and being matched. We can see how the proportion of riders being matched from the total number of participant riders increases, with a slope of this ratio that tends to go to one, where every rider in the system is matched.

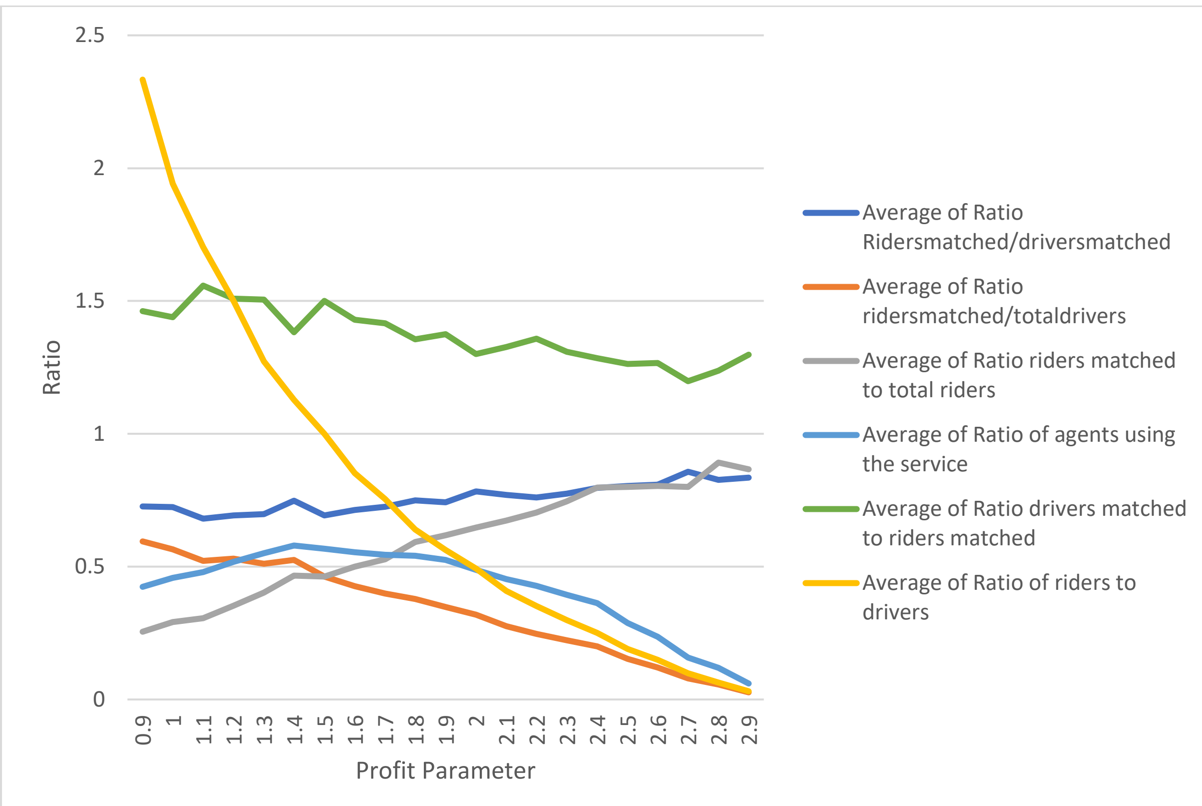

Figure 45. Distribution of ratios of drivers and riders as a function of the profit parameter

If we compare the percentage of agents using the system (number of riders and drivers matched over total riders and drivers participating), we can observe a curve of the percentage of agents using the ridesharing system (Figure 46). It has a maximum at 1.4-1.5, where we have the same number of riders and drivers. Up to this point, we might not have enough drivers to serve all the riders. After that point, the situation is the opposite, where there might be too many drivers for the set of riders, and some of the drivers might not be utilized. It is important to consider this maximum, even if it is not the best one in terms of profit. It would be very interesting to consider in situations where we would like to maximize the usage of ridesharing system to reduce the number of vehicles in the system, if the system is subsidized, or if we would consider a public company as a service provider of shared-ride mobility.

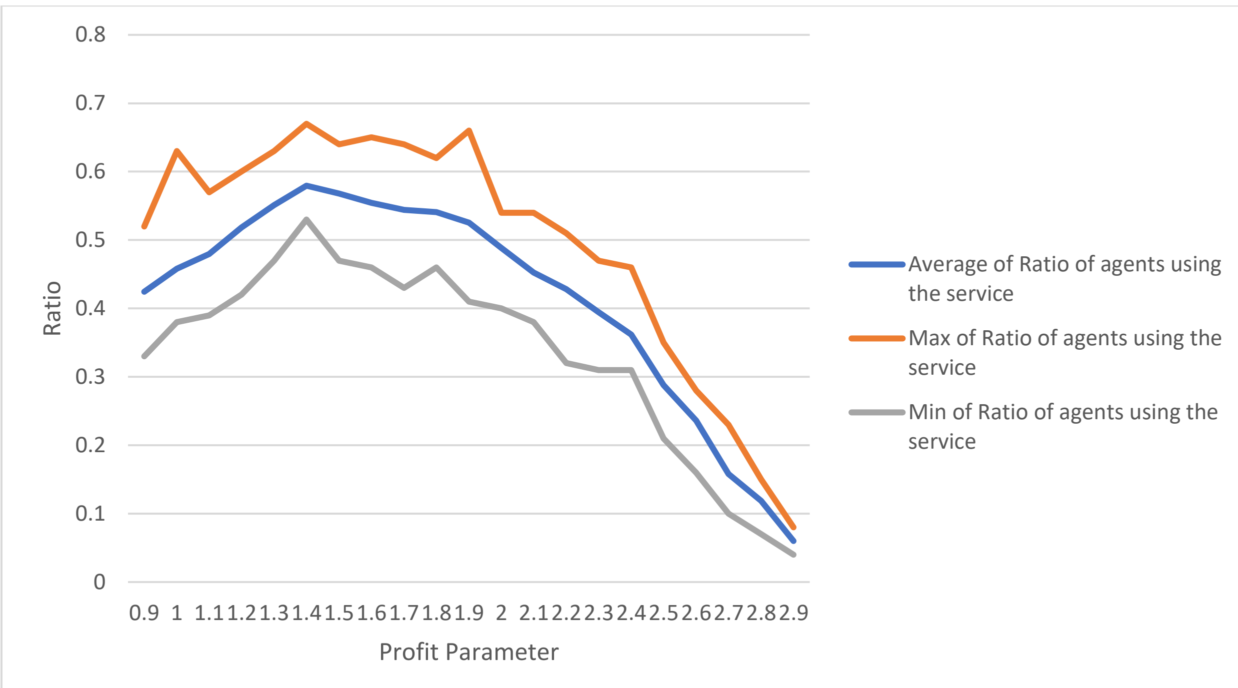

Figure 46. Maximum, minimum, and average distribution of the percentage of agents using the system as a function of the profit parameter

Moreover, if we consider the variability effects mentioned earlier, there is a difference of about 20% between max and min, and 10% with the avg. These differences get smaller around 2.5 where the number of riders starts getting smaller, and as a result, the % of agents using the system too. We could infer that even if the average gives us some information of the best scenarios, there would be some margin for the service providers to increase their impact and improve the number of agents using the system, even in situations close to the maximum profit.

The formulation presented and the module of the system cost analysis allows us to obtain the profit for each situation. This number is obtained considering the revenue and the costs of the system. We can further analyze these different curves to obtain the optimal values for each curve. As initially commented, the value of the profit parameter of 2.2-2.3 gives the highest profit, however it´s important to consider which value of alpha gives the highest revenue and compare with the costs' distributions (Figure 47).

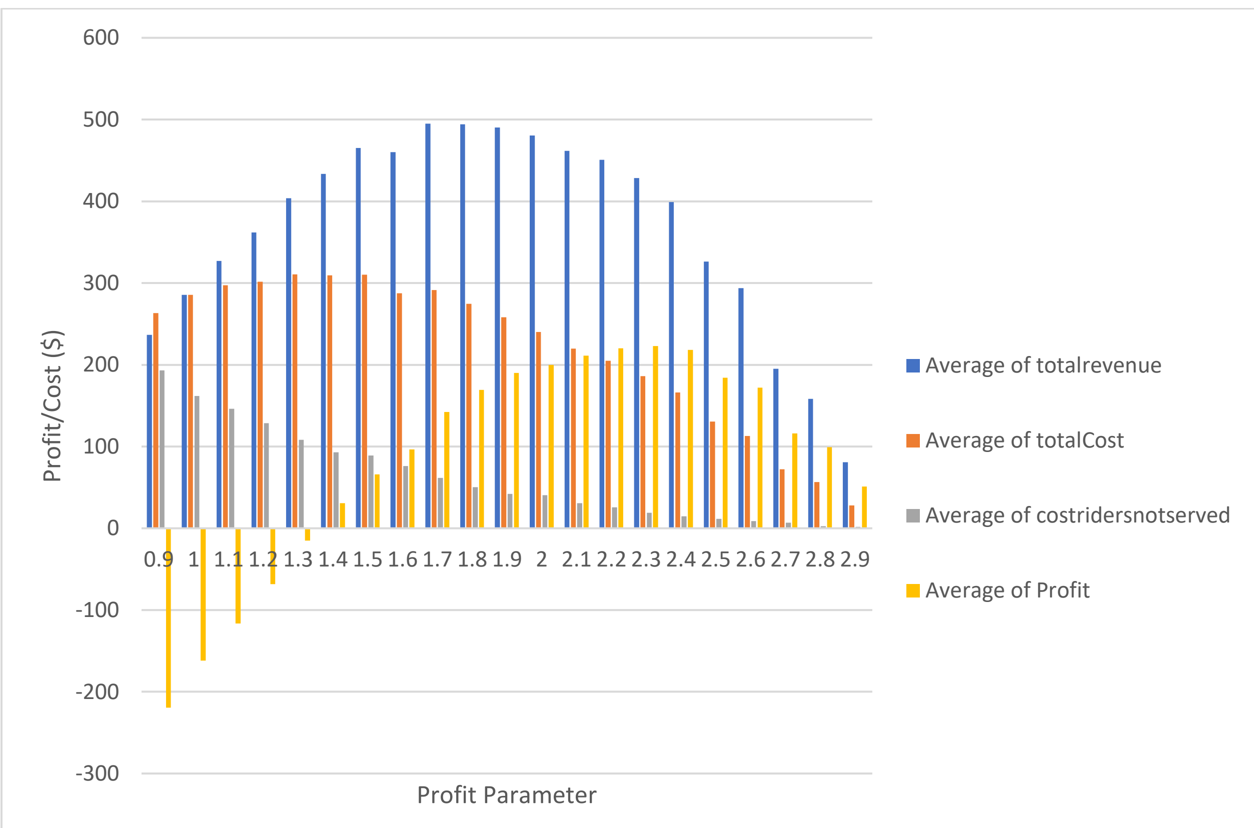

Figure 47. Profit, revenue, and cost distributions depending on the profit parameter

On the one hand, revenue is a curve with maximum around 1.7-1.9, point where the number of riders and drivers using the system is very similar. On the other hand, cost is a curve with a similar shape, however it is displaced to the left from the revenue with a maximum around 1.3-1.5., and the extra costs due to more riders not being served is a decreasing curve. That is, as we increase the number of drivers, less riders will be left without a ridesharing trip. As a result, the best alpha in terms of profit is at 2.2-2.3. This means we have more riders than drivers, enough riders to have a good revenue, and enough drivers so that riders are served, implying a higher profit and less costs for riders not being served. However, if we could reduce costs while maintaining a similar ratio, we could displace the maximum alpha profit to the left, increasing the number of agents actively participating in the ridesharing system.

Finally, we can consider the variability of the system with the profit information similarly to the agents' percentage. We use the average profit of the system to determine the best profit parameter of a ridesharing provider. However, it is important to consider in which situations we can obtain the maximum and minimum profits, to see if a service provider could benefit from the differences and target their services to the ones that could provide a higher profit (Figure 48). If we compare the curves, we can observe similar shapes between them. The maximum and minimum curves would seem a little bit more irregular, with sharper picks, whereas the average makes this information smoother.

The value of the profit parameter of 2.2-2.3 gives the highest average profit, however, with the values of 2.1 and 2.4 we can obtain a higher maximum profit. This might infer that as a service provider we could select certain scenarios where we could obtain a better profit.

We can also see that 1.9, 2 and 2.3 have almost similar max profits, however, they have a higher discrepancy with the min profit, being 1.9 the one with the highest differences. We ca infer that there are other profit parameters that are better with lower costs, better agent usage, but some of them could also have a higher risk involved, where targeting the wrong agents could mean a worse profit situation.

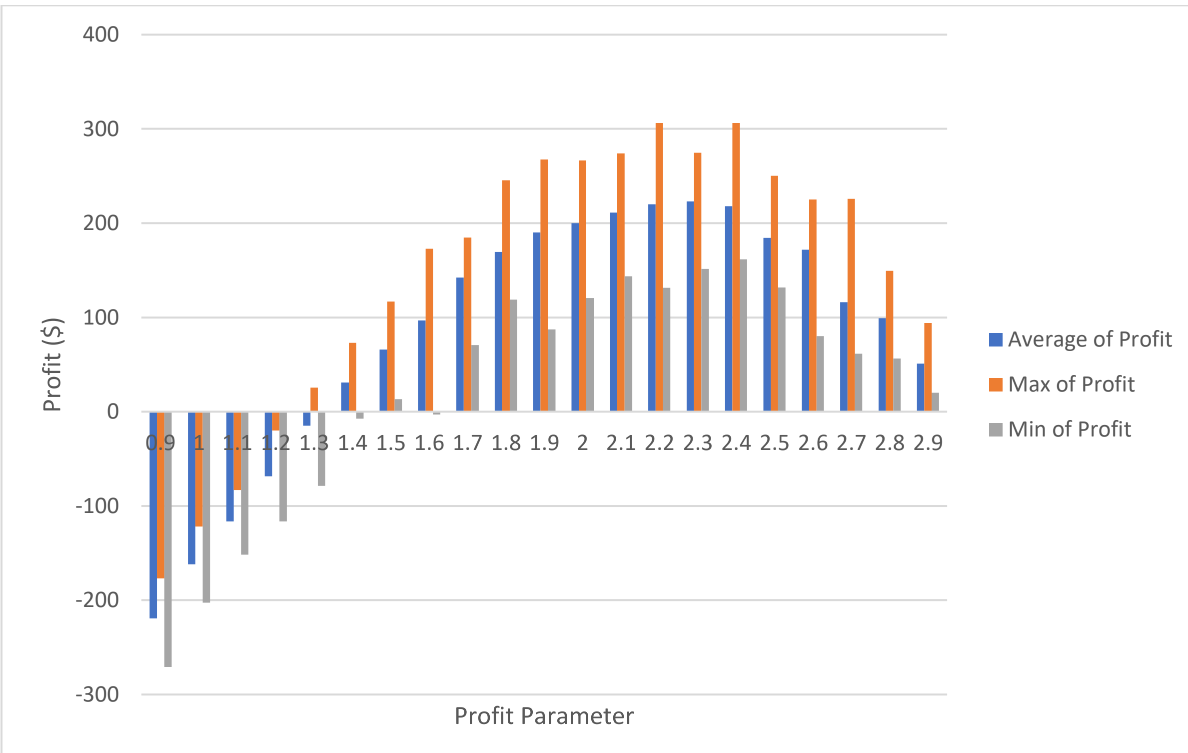

Figure 48. Maximum, minimum, and average distribution of the profit of the ridesharing system as a function of the profit parameter

Case study 3: Optimal Fleet Size for Shared Autonomous Fleet System

The first two cases were fundamentally based on the concept a service provider managing a shared system where people were matched depending on their trips. As we have mentioned, the future of transportation could revolve around three transformations, autonomy being an important one among three. In this case study, we analyze a situation where we have a service provider operating a fleet of autonomous vehicles that give service to a demand in a network.

The concept of this mobility scenario is based on a car sharing transportation system where each agent will own their own vehicle, and then they will share a fleet of AVs for their trips. In this case, we apply the concepts and conclusions obtained from previous scenarios. We apply a modified version of the framework, which fundamentally uses the same concept of matching users with the AV with the lowest trip cost (Figure 49). We take into consideration the generation of the fleet of AVs in our database, the generation of a depot centered in the network, a flexibility pickup time from the users, extra pickup and drop-off times, and the use of the last vehicle usage cost function of electric vehicles for the AVs.

The rest of the elements from the network are very similar. However, there are some more modifications in the ridematching process, as we have to make new implementations in the generation of empty trips of AVs, and new matching possibilities to increase their reusability; the vehicle cost considerations, as we have to include a new type of vehicle; and the cost analysis, where we set a price and compare the cost of using the ridesharing system versus everyone driving alone. We also apply the distributions and the conclusions obtained from previous cases, in terms of the network, trips and pricing.

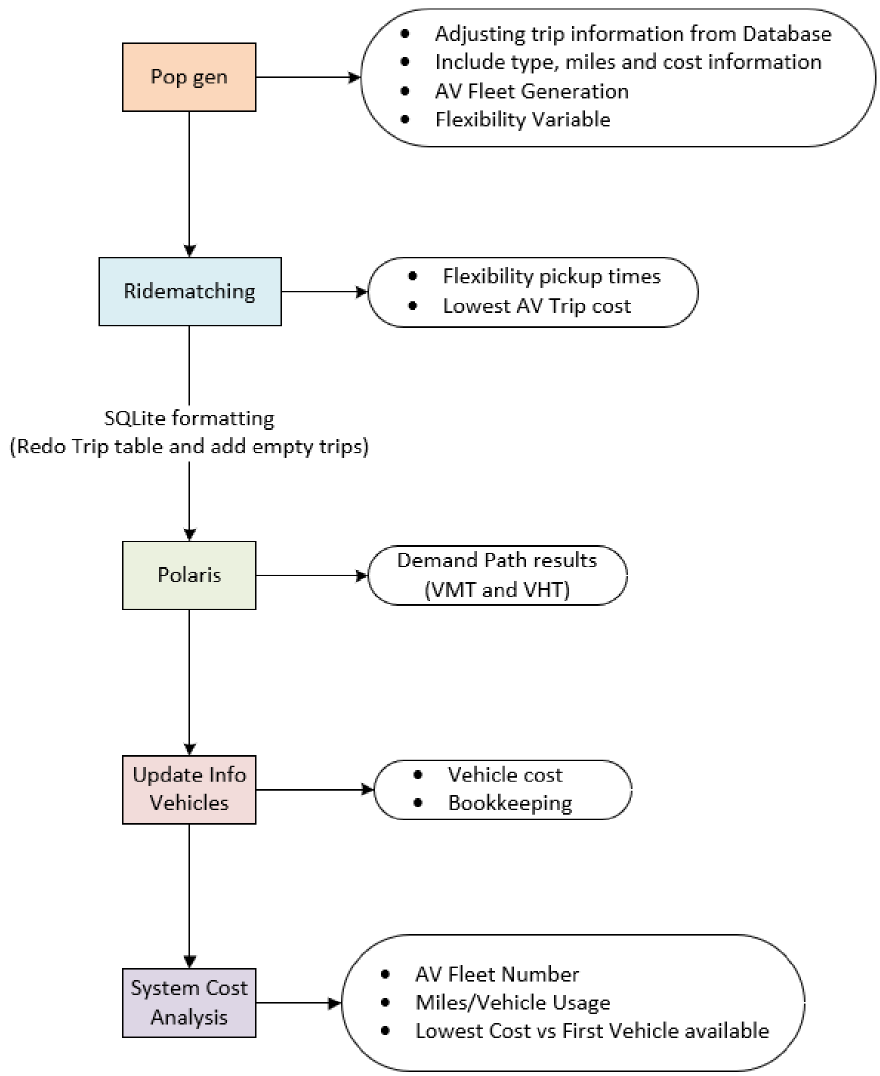

Figure 49. Shared autonomous fleet system diagram

In this case, we test the AV fleet system in a 10 by 10 node network with 180 links ant 360 locations (Figure 50). We generated 100 trips for this network, of 100 agents who are part of the ridesharing system and own their vehicles with assigned vehicle type and initial odometer. We created one depot located in the center of the network, which is the origin of all the initial trips from the AVs. These will then be shared by the agents of the system for their respective trips, selecting the lowest cost autonomous vehicle trip. We test the vehicle cost usage framework with different vehicle sizes and obtain the benefit cost analysis results considering the optimal alpha parameter from the previous case study of 2.2.

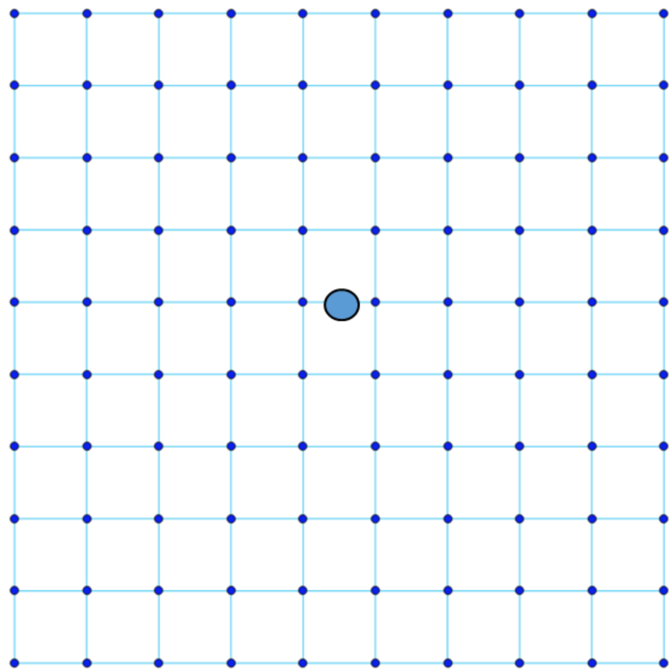

Figure 50. Shared autonomous fleet system network with 100 nodes and one depot location

The first objective from the point of view of the framework would be to serve the maximum number of riders from our demand. Even from the point of view of the service provider, serving more people would mean more revenue. However, in some situations this would imply an over-consideration of the number of AVs on the fleet to, which would involve extra costs of having too many extra vehicles. These considerations will be later considered with the system costs analysis information.

Given the results of the ridesharing system with different AV fleet sizes we observe that the more AVs that we have in our supply, the more riders that we can serve (Figure 51). We reach the maximum number of 100 riders served with 35 autonomous vehicles, approximately a third of the number of vehicles needed. After this point, and as a result of the vehicle cost trip optimization of the framework, any extra vehicle included in the fleet will not be matched with the riders, as there would be a lower cost alternative within the constraints of the system and rider's options. Those vehicles would stay in the depot and would be considered as AVs not used. The main result obtained would be that in this type of systems we would be able to obtain a similar level of service with a much lower number of vehicles. We can increase reusability of vehicles and increase their total efficiency.

In this type of carsharing scenarios, we can define a replacement parameter (σ) as the ratio between the personal vehicles needed to fulfill the trip necessities of a certain population, and the equivalent number of shared vehicles needed while maintaining a similar level of service. As a result, we obtain in the optimal scenario from the results of the application of the framework and the simulation, a replacement ratio of 2.86 for each autonomous vehicle.

$$\sigma = \frac{Personal\ Vehicles}{Autonomous\ Vehicles}$$

This value is obtained taking into account the number of vehicles needed within the time limitations. Thus, the starting time of the trips and their travel time per trip are important factors in obtaining a high replacement value. We can also adjust this replacement parameter to give it a temporal relationship, depending on the starting trip density distribution. If we divide σ by the total time of starting trips, we will obtain a value of replacement depending on the time span where trips would be generated σ_1. With this adjustment we can capture the impact of the time separation between trips. If that time is very long, the replacement value would be lower, which would mean that the benefit of the sharing system would be lower. With that consideration we obtain a value of σ_1 of 3.5 times per hour, which means that the replacement of vehicles is even bigger as we are considering a shorter starting trip distribution. Also, this type of network facilitates the replacement of vehicles, given the distribution of trips and a reduced trip travel time.

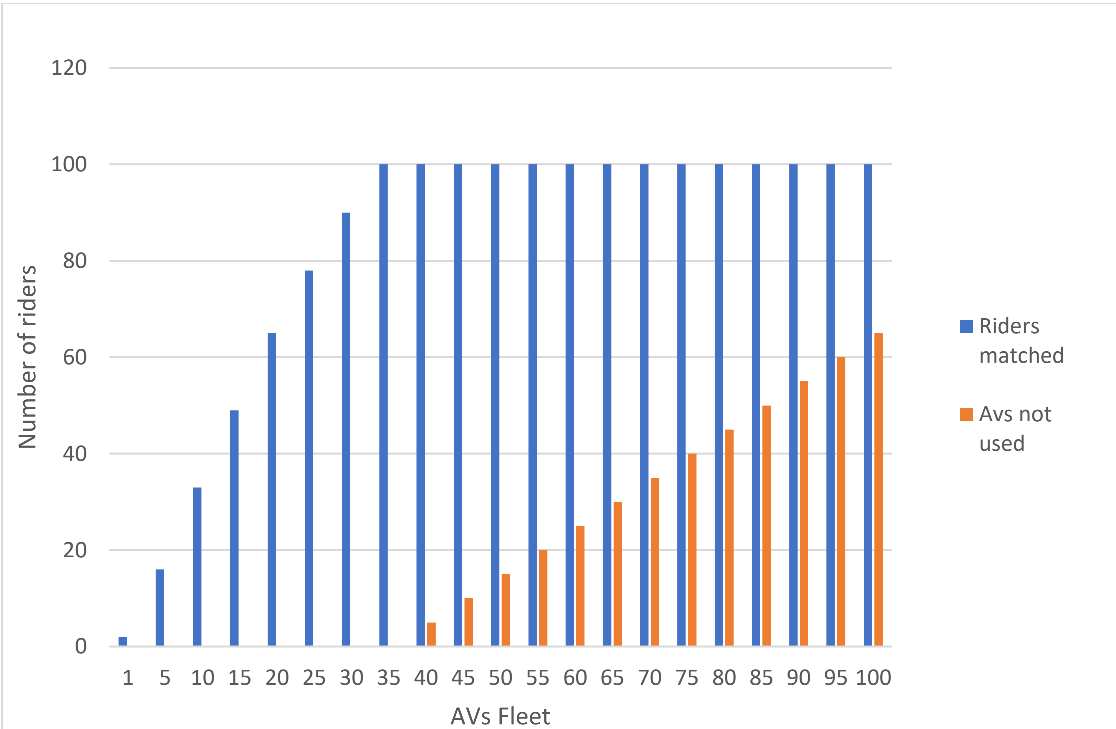

Figure 51. Distribution of riders matched depending on the AV fleet number

Similar to the results obtained from the case one study, here the implementation of a ridesharing system also implies an increase on the miles that the vehicles drive. This is particularly important, as it helps to confirm one of the hypotheses of this dissertation, which is that with shared and/or autonomous systems we would have vehicles driving more miles, and as a consequence, a vehicle cost analysis is even more important. As we can see in Figure 52, the more AVs that we have on the system, the higher that the VMT is. We can compare to the initial cause which would be the one with no AVs and everyone driving by themselves.

The VMT stabilizes at the value of 35, number after which, if we had more AVs, they would not be used. This is the reason why in the figure 51, the AV fleet size jumps from 35 to 100, which would be the maximum number of AVs: one for each rider.

We also represented another situation to compare with, which is the situation where the AVs are matched with the riders without consider the vehicle trip cost optimization. In this situation, noted as 100', the vehicles are assigned to the riders according to the first vehicle available. As a result, on every simulation, all the vehicles of the AV fleet will be always used up until this value of 100, because they would always be matched with the AV waiting to be assigned. The riders will not have to wait for an AV but with the drawback of a much higher cost associated. It is also in this scenario where we see the highest VMT. It might represent a reflection of what could happen if we directly apply the AV ridesharing systems without consider any usage or cost optimization. This is exactly one of the issues of including new ridesharing technologies analyzed in this dissertation.

The empty VMT curve gives us information about the trips that the AVs make without a passenger. As we have more AVs, the value increases with the maximum at 35 AVs, where all of them are used. If a rider does not find an available AV, the agent will do the regular trip with their own personal vehicle. We can infer that the VMT associated with the riders is always constant for their part of their trip, and only changes with the miles associated with the empty trips. In a similar thought, the case 100' has the highest number of AVs used and also the highest empty VMT.

In terms of mileage per vehicle we observe how the more AVs in the network, the less trips are done with a conventional one, and individual usage per vehicle increases. This result reaffirms the idea that ridesharing systems, especially the ones associated with autonomous vehicles increases their usage in the same time frame, which is better assessed with a vehicle cost usage optimization. Finally, we can observe that the empty miles per AV initially increases as a result of a low fleet size. However, once there are enough vehicles in the network to start optimizing the trips, this value decreases until it reaches the optimal fleet size for vehicle use and profit, as we will analyze in following cost analysis results.

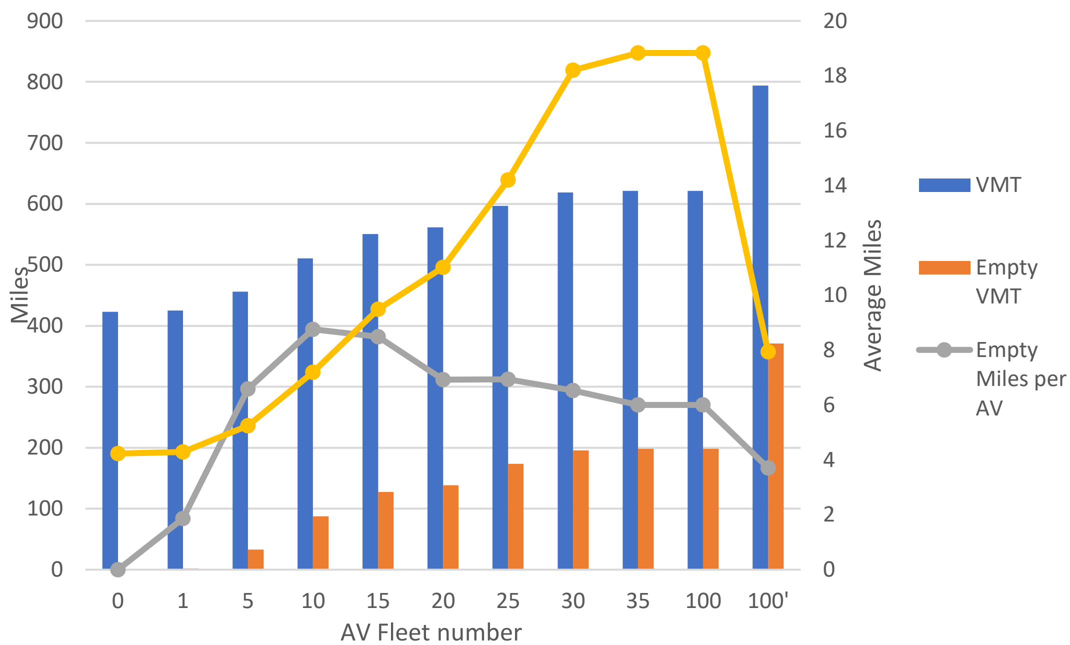

Figure 52. Total and per vehicle mileage distribution for different AV fleet sizes

Given the information about the trips and vehicle usage we can obtain the results of the costs, benefits and profit obtained from the point of view of the service provider, given the formulation presented in the chapter 4. In this case studio we take special consideration in the cost of the AVs not used in comparison with the costs derived from the riders that could not be matched. In this case studio we are not optimizing a profit parameter, so we use the optimal derived from the previous case. As commented in the system cost analysis formulation, we present the profit of the service as the difference between the total revenue and the cost, which at the same time includes the cost of using the vehicles, the extra costs derived from the riders not being matched or the in that fleet number scenario.

The optimal number of vehicles in terms of the profit of the sharing system coincides with the optimal in terms of users matched (35 AVs). The profit curve is initially negative, given that there are too many riders not being served, and then it increases until the optimal and starts decreasing again. Is at this same point where the revenue is maximum and after that it remains constant. As there are no more riders to be served, any new AV will not give any extra revenue.

The cost of unused AVs that is important to consider, as it is a determinant of setting the fleet size. However, there are conceivably several strategies that can be implemented. It is complicated to add a cost of the unused vehicles when the framework is based on obtaining their cost as of their usage, especially when we do not have information about the type of trip or use that these unused vehicles would have had. We could derive its cost by considering an average trip in the network or average use, however, we would be missing the opportunity cost of that vehicle in a trip and their derived wear and tear. For this reason, in this case we consider the equivalent use of a regular vehicle during the morning peak, and the ownership cost derived from that equivalent mileage for the vehicle type. It needs to be emphasized that it is particularly important to consider an equivalent cost to adjust the slope of the total profit curve after the optimal point, but it will not have a significant effect on the AV fleet size or the shape of the curve. Also note that demand uncertainties are a reason for having extra fleet size. Some of these additional effects are not studied here.

The total cost is always increasing because as we have more AVs the costs always increase: initially we have a high cost of riders not being served, then the more AVs we have in the fleet the more it costs using them even if there are less riders not being matched, and finally, after the optimum, the cost of riders not being served goes to zero, but then the extra costs derived from AVs not being used has more importance. It is of special importance the optimal AV fleet value which appears as a singular point in the different curves: the extra costs concur at a value of zero, as a result the total cost is only the cost of using the vehicles, the revenue has its maximum value and so does the profit.

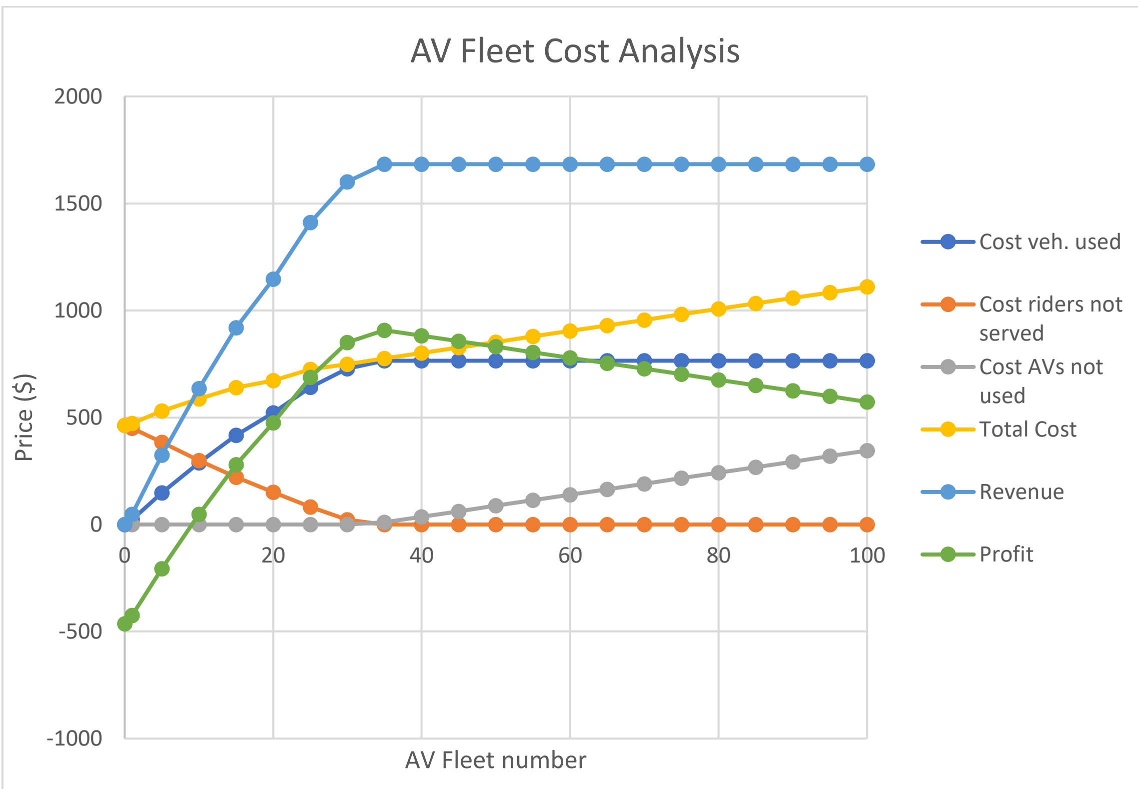

Figure 53. Cost, benefit, and profit curves as a function of the AV fleet number

After analyzing the number of AVs needed, the usage and cost interactions, we have observed that can provide a similar level of service with 35 AVs instead of the 100 conventional vehicles needed in the first place. There is an extra benefit derived from needing less vehicles with the same transportation network and demand, and there are some steps in between those two mobility scenarios. If we analyze the total number of vehicles needed, we can see how by slowly increasing the number of AVs, the number of personal vehicles (PV) and consequently the total number of vehicles used drops (Figure 54). As also commented in Figure 51, the more AVs in the fleet, the more agents are provided with a trip, the less PVs needed, and the less vehicles are used.

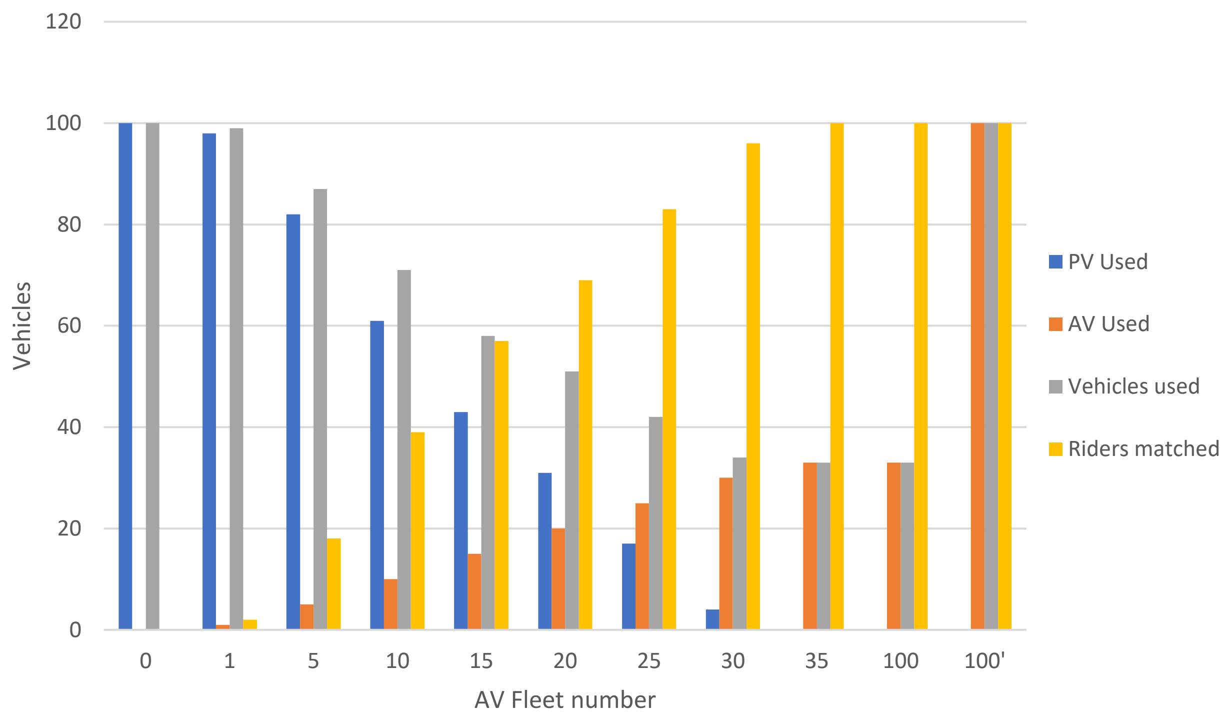

Figure 54. Distribution of Personal Vehicles (PV), Autonomous Vehicles (AV) and vehicles used in comparison with the riders matched and the interaction with the AV Fleet number

It is true that this AVs are more used individually and in average, however, this type of transportation system allows an easier and better control of their costs and use. Especially if we combine the systems with a cost optimization where we can consider the trip cost depending on the vehicles. Here we present again the scenario 100', where we also have 100 AVs, but vehicles are matched with the closest AV possible, and not considering their cost.

As a result, if we consider this extreme case of having one AV per rider, all of the vehicles are used instead of the conventional cars. We have just transferred the use of individual vehicles to a service provider without obtaining any benefit. Even more, we add extra costs due to the extra empty miles associated to the AVs. It is utterly important to combine new shared mobility systems with a proper cost usage framework, in order to optimize the matching and use of vehicles as presented in this research.

Finally, given the information about the costs for the vehicles in the scenario with only personal vehicles and in the optimal case with 35 AVs, we can analyze and compare the estimated monthly cost of owning a vehicle versus using the AV system (Figure 55). The results presented part from the point of view of the vehicle, which given the trip cost optimization result in the lowest cost for the vehicles.

The cost associated with owning the vehicles also takes into consideration their use and the cost of the time needed to drive them. Then, we calculate the average cost of operating an AV with the electric vehicle cost function, and the estimated cost if we used a cheaper cost function similar to the regular car (cheaper AV). We calculate and compare with the average cost of owning and operating a PV.

In the first scenario, we analyze the cost of owning the vehicles where all the agents use their personal vehicle. Given the vehicle cost functions associated with the distribution of vehicles from the NHTS and the equivalent vehicle usage, we obtained a value of approximately $550 per month, with a vehicle use of about 400 miles per month. This value is a bit smaller compared with the monthly used usually considered which should be around 800 per person which would give us a value closer to the 800$ of ownership cost by AAA Then we can obtain the equivalent monthly cost of using AVs and compare. There are, however, many possibilities in terms of their cost, especially considering the idea that their technology is still in progress, and the type of networks where this type of systems will be applied.

If we consider the usage of vehicles obtained from the framework, their cost per mile, and the extra VMT based on the empty miles driven by the AVs, we can estimate the monthly cost for each user. The initial cost associated with AVs might be considered very high, as it takes into account the vehicle usage cost function associated with early stages of electric vehicles. The idea behind the use of AVs is that their cost associated would tend to the one of a regular vehicle. Thus, we can generate situations where the cost of usage per mile would be the highest for one of the newest electric vehicles (expensive AV), or what it could become in the future, where the cost may be comparable to the conventional car (cheaper AV). In both cases the cost of using vehicles is cheaper in the case of AVs, but even with the cheaper version of AVs, the cost of using them is lower than the operational cost of using the personal vehicles.

We can infer from this information that it might be possible a future of shared systems where car ownership is switched from a personal to a service provider perspective. These situations might need more research to reduce the cost of using AVs, which is significantly related to the cost of fabricating them in order to reduce their depreciation, to make their cost per mile closer to the current vehicles. This allows us to combine this monthly subscription idea with the one of a limited mobility portfolio situation with AVs. This gives us the possibility of using shared services, where there is space for different companies and subsidies to get benefits of using less vehicles.

This would not only increase the usage of vehicles, which increases the average trip travel time and distance, but also the difficulty of implementing this type of systems. Empty miles would increase a lot, and so will the usage and costs of vehicles, and more resources would be needed to create more depots to park and deploy the AVs and reduce those miles. Finally, the whole system benefit is based on the implementation of the framework presented in this dissertation, where vehicles and trips are optimized considering a vehicle usage cost function.

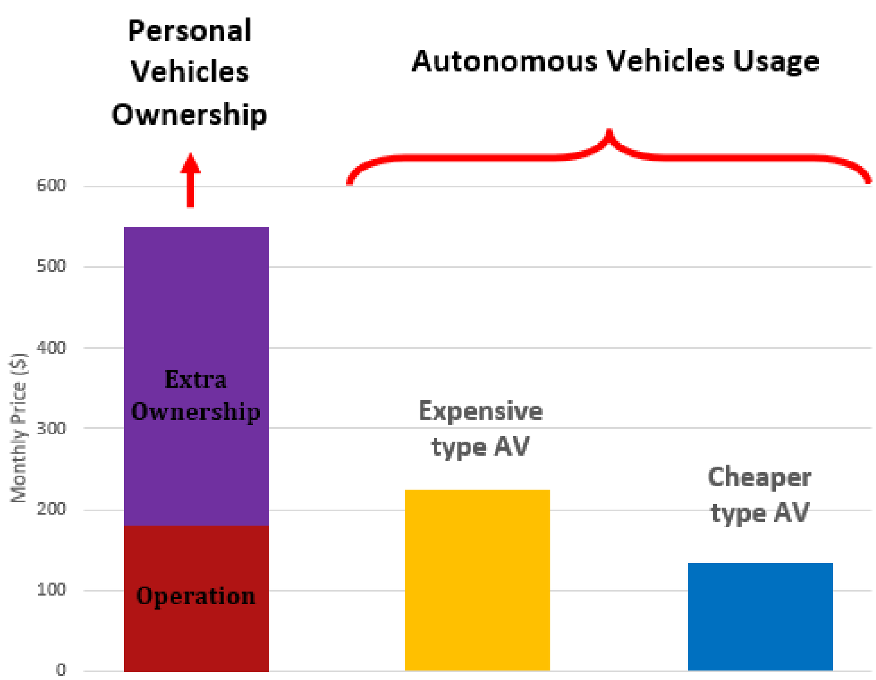

Figure 55. Monthly vehicle cost for different scenarios of personal vehicles or autonomous vehicles

In this scenario, all the nodes in the network are well connected, as a result given an appropriate number of AVs, all the riders where matched with the use of only one depot. Bigger networks might have node connectivity issues and they will benefit from having multiple depot stations.

Moreover, extra costs such as pollution or parking are not directly considered even if they could be easily included with a proper model associated with the per mile cost. However, as we have observed the number of vehicles used to provide a similar level of service is much lower than the ones with the conventional vehicle use, an especially with the use of AVs, the importance and use of those models would need to be reevaluated in these situations. If the number of vehicles needed is much lower, the parking associated with those vehicles would also be less important, especially considering the use of depots to store them most of the time. In terms of pollution, the emissions associated with the use of AVs is much lower if they are electrified and is usually caused by vehicle manufacturing and production of electricity, and not by the use of AVs themselves.

Case study 4: Shared Autonomous Fleet System in Irvine Network

The case studies up to this point reflect very important findings in the use of shared transportation systems and the application of a framework based on the vehicle trip costs. We have observed different impacts, and the importance of having a network big enough to reduce secondary effects due to its shape or size, but at the same, not too big so that the trips are too long for autonomous vehicles. In this last case scenario, we test the framework with the real network of Irvine and its corresponding demand database, presented in the chapter 4 of this dissertation, also as a part of the Autonomicity project. This network is a little bit bigger, with more nodes and trips. The objective is to present similar results as the ones already obtained, in terms of sharing optimization and vehicle reduction. In particular, we test the autonomous vehicles fleet service as a car sharing system to be used for personal trips.

The network presented corresponds to the triangle region of Irvin city. In this study area, there are 34 TAZs, 1,038 nodes, 1,800 locations and 1,531 links. The study area is bounded by three major freeways (i.e., I-5, I-405, and I-55) and toll roads (i.e., California State Route 73, and California State Route 261) (Figure 56). Each of the links connects two nodes, and it is populated with several locations in both directions, which serve as the origin and destination of the trips. In this case we also select one depot centered in the network as the spot to keep our AVs, and the initial origin of their trips.

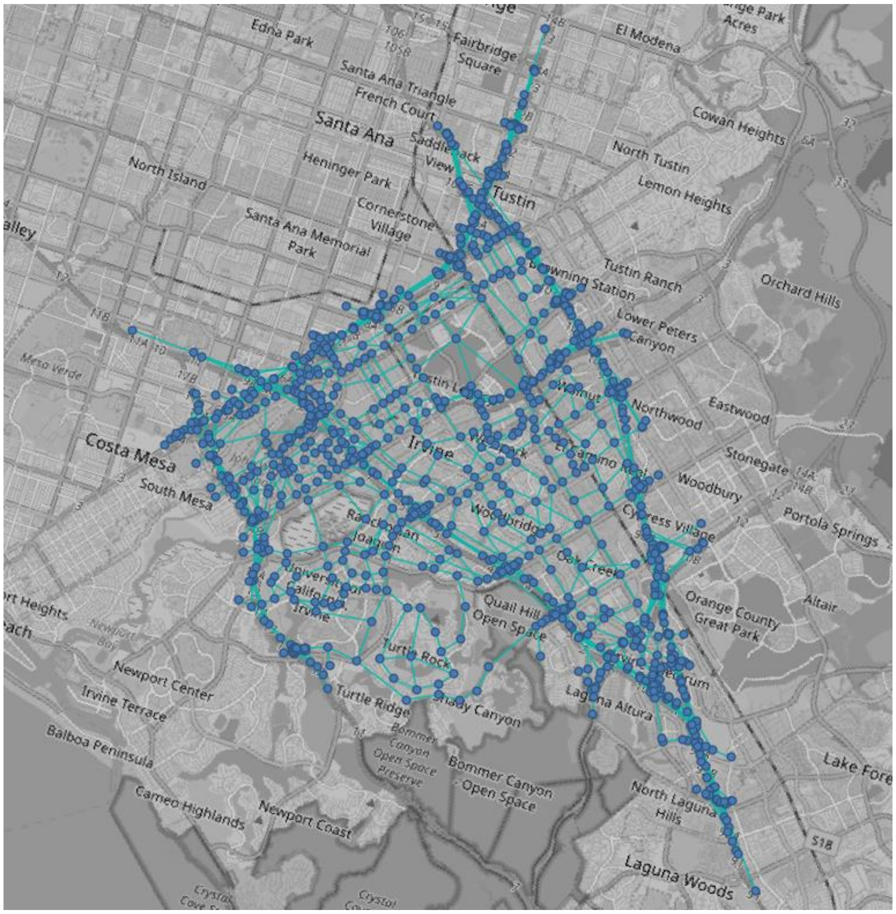

Figure 56. Irvine network representation with node and link identification.

The network uses current demand levels for travel desires and includes activity generation capabilities that are based on the California Statewide Travel Demand Model (CSTDM). We applied their synthetic population as the original pool of agents from which we sampled the agent trips for our network. The origin and destination tables are also from CSTDM based on which we performed a sub-area analysis and estimated the internal and external trips for the study area. In this study we are focused particularly in the most representative trips from the morning peak, which correspond to commuting trips inside our study area. The whole demand including all kind of internal and external trips (passing through, coming in or going out), and comprises roughly 400,000 trips in the morning (from

6am to 10am). In order to consider a more specific target of our sharing system, we focus on the internal trips generated in the first ours of the morning pick. We consider 5,000 trips which could really benefit from our ridesharing system. If we consider too many trips, they will be very separated in time. It will be easier to match with AVs but then the optimization will not be as important. Also, considering external trips might be an issue, as other type of assumptions would be needed, in particular in terms of generating more depot locations or stations at the entering nodes of the network.

Similar to the results obtained in the previous case, we would have a similar level of service with about a third of the number of vehicles (Figure 57). In this case, with less than 1,410 AVs we would be able to ride the demand considered in this situation with a similar level of service.

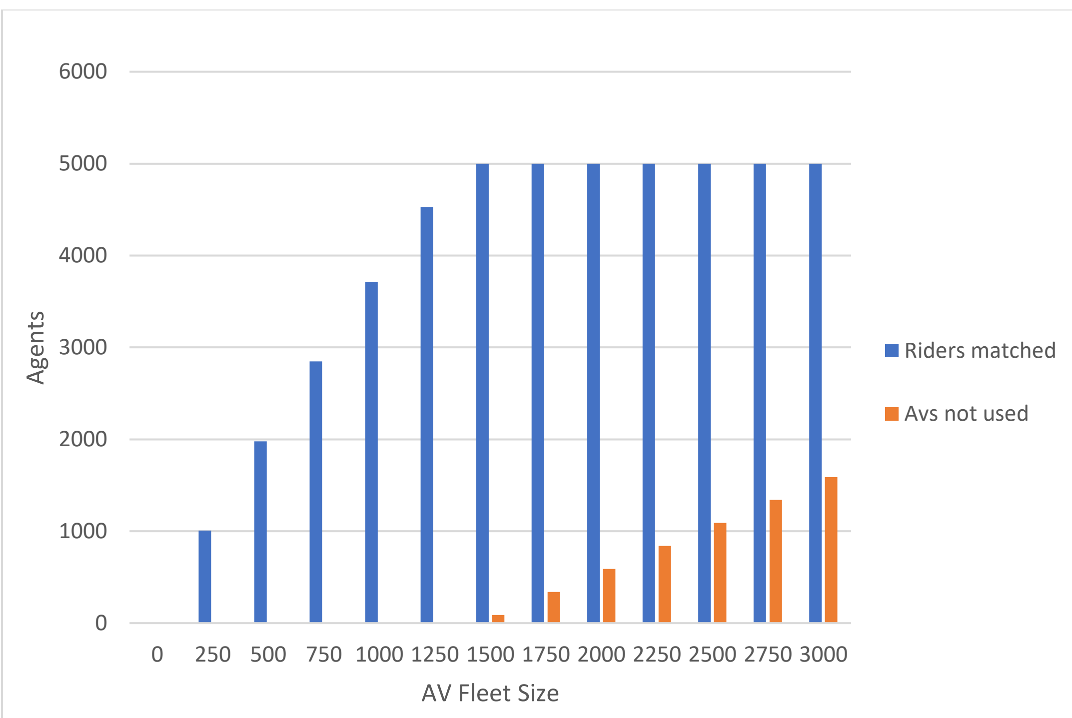

Figure 57. Fleet size optimization distribution for the Irvine network

The results obtained are similar to ones obtained with the test network, however, some differences can be attributed to network constraints and the heterogeneity of the trips generated in this situation. We can also see that after that optimal number all the AVs added to the network will not be used and they will stay in the depot, adding extra costs into our service provider. Comparing the results with the ones obtained in the case 3, we can see how having a similar density of trips in terms of time and space is important to reach similar level of results. Not only the network shape and the connections are important, but also how the trips are distributed affects the usage of AVs in the network.

If we analyze the replacement of vehicles in the optimal case of number of AVs used, we obtain a value of σ of 3.5. It shows the impact of using AVs to reduce the number of private vehicles needed. The small difference with the test network of case 3 could be attributed to a much bigger trip database, a higher heterogeneity in the trip distribution and to the irregularities of the network compared with the squared one. If we consider the starting trip time distribution, we obtain a value of σ_1 of 2.66 times per hour. We could infer from this value that, in this situation, vehicles starting times were more separated, which made it easier for users to be matched with AVs. However, due to the limitations of the dataset distributions, the per time replacement is affected, showing a lower number.

It is also very important to notice that in this case study, and in a similar way in the case study 3, the optimal number of AVs needed to provide a similar level of service strongly depends on the flexibility of the users. In this study, this flexibility is translated as a small variability on the pickup times of the user. The more flexible the users are, the easier it is for them to be matched to an AV during their time constraints (trip departure necessities).

However, other factors have importance in this process of matching, such as the network constraints and the density of trips during the time period considered. Even if we consider a bigger flexibility, we will still have to limit the total time period for the trips considered. Hence, the starting time of trips could not overpass certain values and the flexibility would not have a bigger impact. Moreover, considering high flexibilities could impact the quality of the service in the users, making users not want to use the sharing system, and will not be considered as part of this dissertation.

In relationship with the starting time distribution of trips, we also have situations where AVs would have to wait before they are assigned and enroute for the next user. As a result, we would have a total idle time associated with each AV. We would want this value to be as low as possible to reduce inefficiencies in the system. It would have impact in the network and would make it more important to consider parking and/or congestion effects. These effects are not the focus of this dissertation, but we notice their importance in future works. However, more considerations would be needed, in particular more information in terms of current and future parking, in a situation where AVs have more importance, and the ownership of vehicles would change. If we needed less vehicles, we would expect to need less parking, as a result, its impact will not be as important. In our case, we obtain an average idle time of seven minutes per vehicle during the peak hour time period considered. This value could be even improved if we consider higher flexibilities from users.

In a similar way to the ten by ten test network, we can analyze the benefit and cost distribution. We can observe how we obtain similar curves for the costs, extra costs, revenue, and profit (Figure 58).

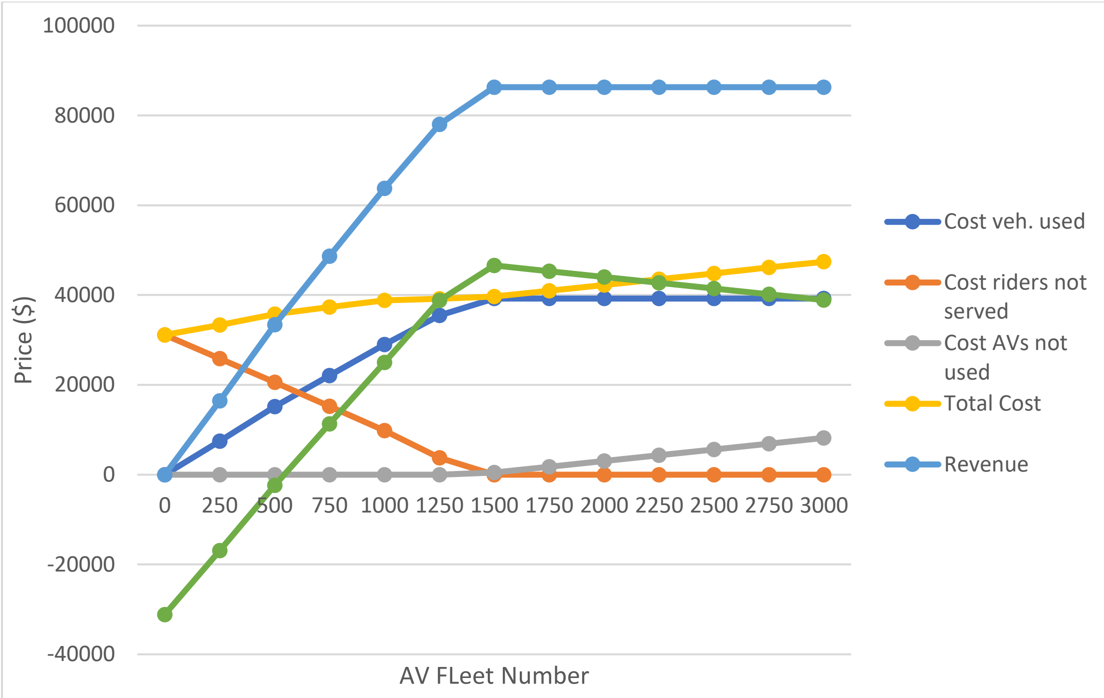

Figure 58. Cost, benefit, and profit curves as a function of the AV fleet number

The distributions obtained are very similar, with an inflexion point in the optimal value for the AV fleet number, which in this case is 1749. At this point, the extra costs added for either riders not being served, or the extra AVs go to zero. Revenue has the maximum value, as all users are being served, and the difference with the total cost is also maximum. Hence, we obtain the optimal value of the AV fleet size with the optimal Profit. We can also notice how the profit curve only reach positive values after 750 AVs, point where almost half of the number of users is being matched with an AV. Finally, if we compare the curves with the ones form the case 3, they are less smooth and show more irregularities, which we can consider a result of using a real network and demand distributions.

Interactive Behavioral Decision Processes

The application of this cost usage framework allows the analysis of the interactions of some elements of the shared mobility systems. There are also presented situations of the simulation where we observe interactions between other elements which would have a behavioral decision making process or impact. In this section, we add some comments on the decision making process and interactions of agents, as they make use of the sharing system, and some of the implications of being part of it.

We refer as an agent to any person that is considered to have the possibility to be part of the sharing system. These interactions would determine how the model is developed and the importance of this type of analysis from the point of view of the company in charge of the system. The interactions presented take into consideration relationships and situations from the simulation itself, but also try to give a glimpse of possible scenarios that could happen in the reality. This includes algorithmic hypothesis and simplifications, and also behavior and personal choice considerations. The diagrams presented next include the behavioral process of agents being part of the ridesharing system, and their taxonomy of vehicle ownership

Diagram behavior agent

This first diagram starts with the very first and simple question: Will an agent consider using a ridesharing subscription service? For what the possibilities are only two, yes or no. Choosing one option or the other may have different factors. It can be the result of a personal preference, previous experience in the sector, the availability of options for their situation, and even policy implications that can affect their decision making in terms of incentives to use the system or restrictions to not be part of it. These incentives can be related to tax benefits, money, social, and even a personal benefit for being part of the ridesharing system; and the restrictions might be related to reduce the use of personal vehicles, include higher taxes for individual drivers and also the use of congestion pricing for those vehicles.

The representation of the options can be observed in Figure 59. If the agent chooses not to use it as a result of a higher utility from using their personal vehicle rather than ridesharing, they will drive their vehicle and will not be part of the ridesharing system (other policy implications). If a person chooses to use the ridesharing system, then we could have him or her as a rider or a driver and the simulation would start with them. This option selection can be also the result of a similar behavioral model and could be also reviewed with a higher periodicity than the previous one. In this case, however, more importance should be given to the utility of elements related to the trips themselves, the availability of vehicles and options, the generalized cost of using their own vehicle as opposed to paying for the trip, the time needed to fulfill the trip, and even the number of transfers needed.

The importance of these models does not incur only in finding the correct utilities for each element, but also in the importance of the interactions between the elements: how these utilities would change as the system is in place and agents reevaluate their choices. This means that if an agent chooses not to be part of the system, not only we do not have to find them a combination for their ride, but also, they will not be a possibility for other riders, so we the opportunities for other riders to find a trip will be reduced. A similar thing happens when we analyze the utility models to determine if an agent will be a rider or a driver of the system. Changing form one to another not only has individual implications but affects in a similar way what other drivers and riders and do. Moreover, in certain situations it can develop a cascade effect where many trips can be affected by, as the inclusion or exclusion of drivers and riders can change the matching of immediate agents, which as a consequence affect other agents which were not initially affected.

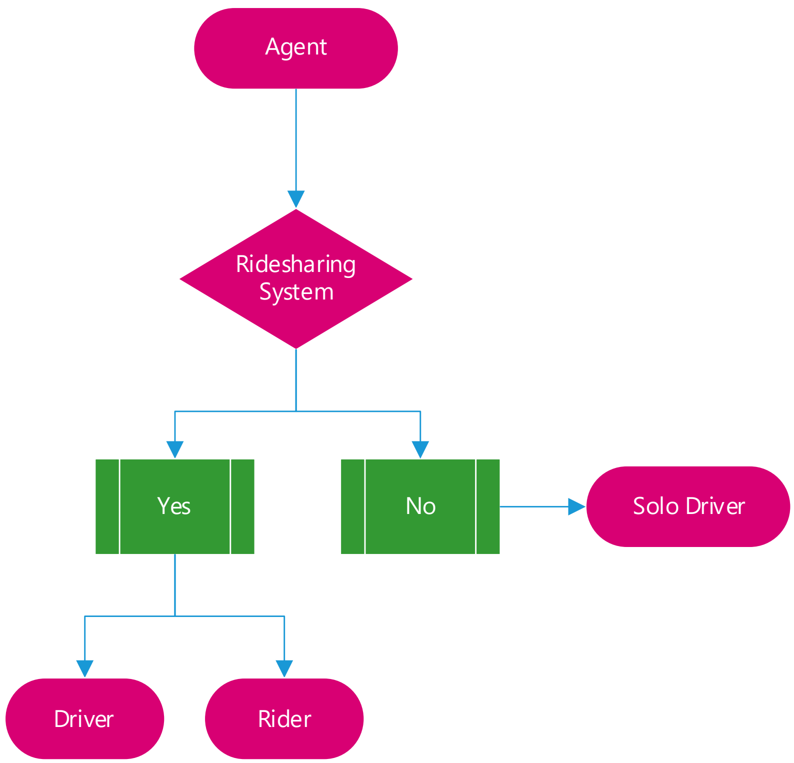

Figure 59. Diagram behavior agent choosing ridesharing system

The next step in the diagram start would be after an agent has decided to be part of the ridesharing system and want to be a rider (Figure 60). Drivers are part of the matching as well, but they play a more passive role where they get assigned to parts of the trips of riders. In this process, each agent considered as a rider in the ridesharing system is presented with a mode combination depending on the alternatives included in the ridesharing system. Each agent can choose to make their trip with the combination proposed or not. These possibilities are considered through an assumption on the rationality of our riders. In the simulation we would consider a choice model where agents are totally rational and thus will choose the option proposed, which is the best mode combination considered with their situation. However, we also consider the possibility of people not being totally rational. In that case they might choose to accept or reject the mode combination proposed depending on the personal utility that they might perceive for the trip proposed with the ridesharing system. These utilities will have a similar set of elements when choosing to be part of the ridesharing system or not and could present differences depending on the moment they are considered.

Therefore, agents which are considered as not following the total rationality of the model will choose to accept the ridesharing option if the derived utility from it at that moment and trip is bigger than the one that they might get by using their own personal vehicle (in the diagram Ur: utility derived from the ridesharing trip; Ud: utility derived from the trip as a solo driver, meaning driving only by themselves). The other way around to reject the model, in which case they will use their personal vehicle as the mode of their trip. Moreover, as mentioned, this personal utility choice can be presented for each agent at each time and for the mode combination proposed. This means that, depending on the number of options and combinations for each agent, every time the combination proposed is rejected, we could iterate through the different options in case one of them might be accepted by the agent. In a similar way, even if the option proposed is accepted, we could iterate through the options to find the one that gives the maximum utility for the agent, in a scenario where we would like to maximize the utility derived from the trips for each agent.

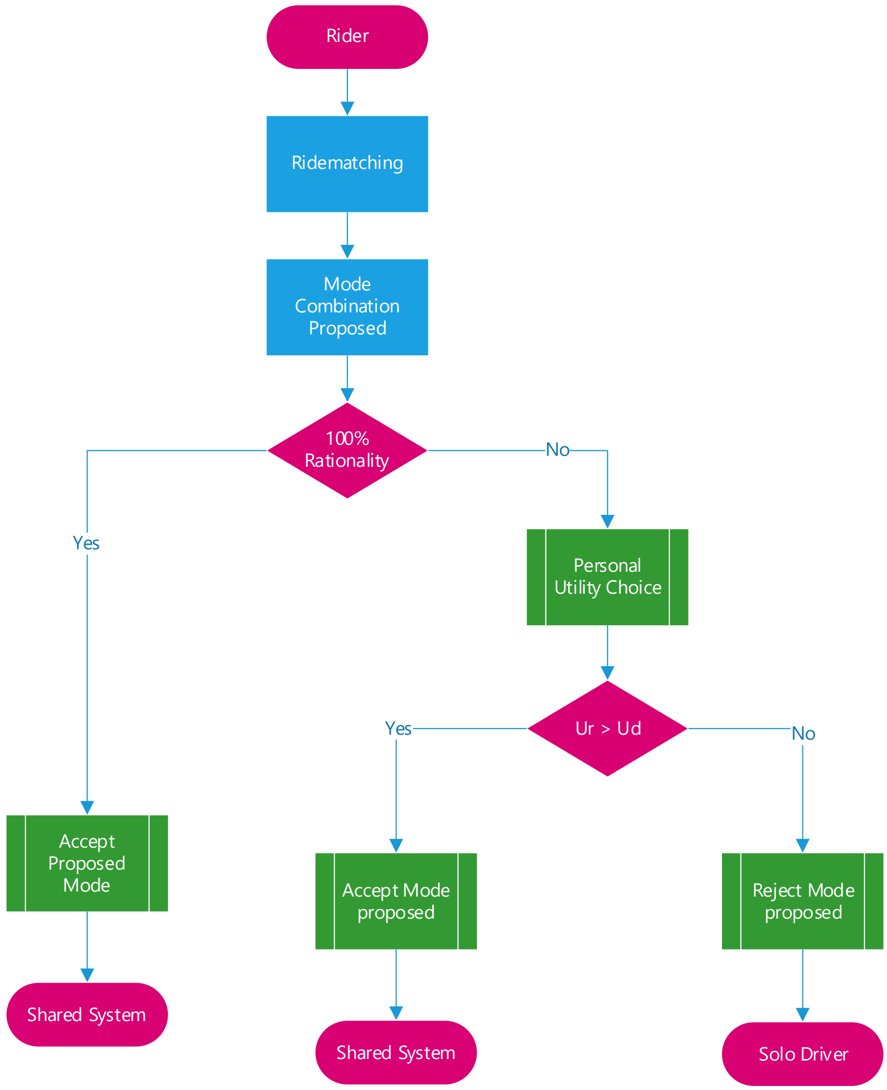

Figure 60. Diagram behavior choice for riders and their personal utilities.

As we have seen, being part of a ridesharing system and choosing in what way incurs in a lot of decisions to be made. In these situations, the behavioral aspects and the elements considered for the utilities for each situation are important, but also to consider when some of these decisions would be done. It is clear that different parts of the decision making would be done at different frequencies. An agent would consider being part of the ridesharing system every one year or six months. Deciding to be a rider or a driver would be something to decide with more frequency (for example, once every one to three months), however, this could also be subject to the conditions and necessities for each agent, like owning a vehicle or not, which could immediately determine their situation.

Finally, if a more complex model is considered where agents are assumed not be 100% rational with the mode proposed from the optimization, they could choose to accept or reject it every day, and even more than once if iterations for different alternatives are being considered. These considerations add another level of complexity and would happen at different time resolutions. It is clear that only by running the system we could actually operate it better. There would need to be some learning observations to determine when to do these decisions, and it would be essential to have a constant monitoring of the system.

Diagram taxonomy vehicle ownership

The ridesharing system is formed by the agents and their decisions. As we have seen, these decisions can be affected by the personal situation of each person and how they perceive the characteristics of the modes and trips. However, not only agents shape how they choose, but also, the decisions that they make and the way the system performs might affect their perceived vision and utility of the modes, and even they might affect other aspects of their personal situation.

One of the most important aspects considered in the ridesharing system is the possibility of reducing the number of vehicles on the road by matching people with similar trips. In this diagram we analyze the possible interaction between agents and the ownership of their personal vehicle. Depending on their use of the ridesharing system and their situation of owning a vehicle or not, they would have to respond to a different question, and they would be assigned to a different agent type or role. These decisions would also be done in a similar way depending on the personal utility derived from using their personal vehicle or the ridesharing mode combination proposed, and would be made at different time resolutions, in a similar way as described in behavioral agent diagram. Thus, to imitate the comparison between alternatives we can consider in a similar way the utilities of each option. We would have Ur as the utility derived from using the ridesharing system; and Ud as the utility derived from owning a vehicle, which would consist in the utility in being a solo driver.

The decision choice process is reflected in Figure 61. In this diagram we start with the very first question, whether an agent owns a vehicle or not, and depending on the answer to that question, we separate into two different but similar processes. If an agent owns a vehicle, the question presented would be if whether they would think about selling it. The answer to that would depend on their personal utilities towards using it compared to using the ridesharing system. If the utility of using the ridesharing system is bigger, then the agent would consider selling the vehicle, make use of the ridesharing system and would be identified as a rider, a driver, or a combination of modes within the system. On the other hand, if the utility of owning a vehicle is bigger, then the agent would disregard selling their vehicle, and would be designed as a solo driver. However, depending on the level of rationality that we assume (as presented in the diagram in Figure 60), this agent could still make use of the ridesharing system in some situations and be designated as one of the agent types from the ridesharing system.

In the second case, process 2, an agent does not own a vehicle. In that situation would they consider buying one? The decision choice process explained in the diagram would be very similar to the previous one. If the utility of owning a vehicle is bigger, then they would think about doing so, in which case they would have the possibility of being a solo driver or a user of the ridesharing system. In the case that the utility of being part of the ridesharing system is bigger, then the answer would be not to buy the vehicle, and the agent would be forced to be an agent from the sharing system.

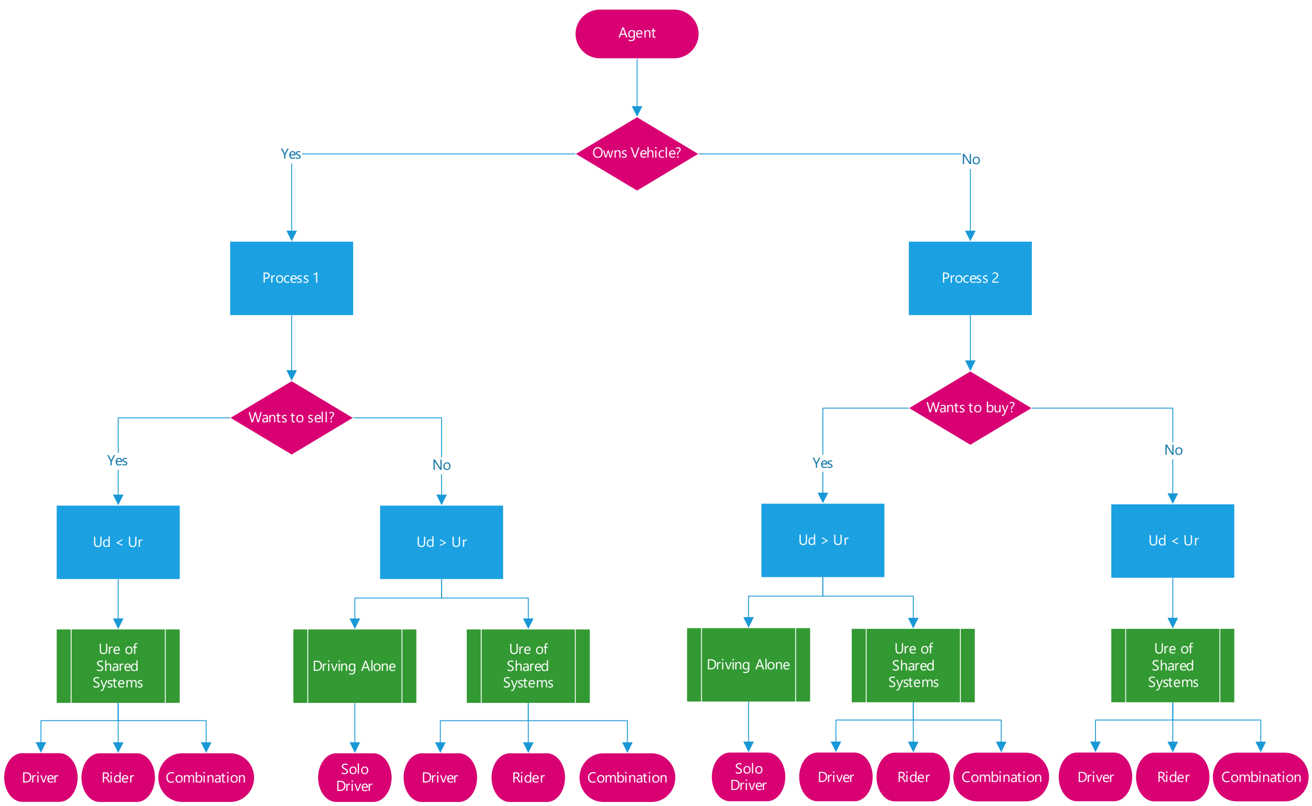

Figure 61. Diagram agent vehicle ownership and agent type determination

The difference with the previous diagram is that in this case the choices might be evaluated every time there is a trip involved but need many repetitions until they are fulfilled. This means that certain agent might own a car, and only after many iterations where the utility of the ridesharing system is bigger, they would sell their car. In a similar way, an agent who does not own a vehicle but given the utilities sees the benefit of owning a vehicle might do it. There are other external factors that might affect this decision and trigger a faster decision, such as the personal situation of the agent which financially speaking make it difficult to own a vehicle, or the necessity of an agent to own a vehicle because the ridesharing system cannot provide a feasible trip for them. In a similar way to the previous diagram, there would need to be some learning observations and it would be essential to have a constant monitoring of the system.

Finally, it is worth mentioning that we could make use of this diagram in the same way in the case of any agent owning more than one vehicle, by considering the purpose trip destined for each vehicle in each situation. Then we would have not only individual temporal utilities for each agent, but also utilities based on each vehicle considered for certain purpose trip. This would be important in the case where an agent would find benefits in not owning a vehicle for work commuting because the ridesharing system would offer good enough possibilities for them to have a competitive utility, and thus selling it. However, in the case they owned another vehicle for leisure activities which would be more difficult to be accessed, they might consider selling one car and keeping the second one.

CHAPTER 6:
Conclusions

This dissertation introduces a framework based on the vehicle usage cost for modelling new shared mobility systems based on the use of shared and/or autonomous vehicles. The focus is on the importance of considering a proper cost model due to the increased usage of vehicles in these new situations. The most general form of ridematching provided considers a many to one scenario, in which each rider can transfer between multiple driver vehicles. More efficient algorithms for more restrictive forms of ridematching are also provided, especially for the case of a fleet service of autonomous vehicles. The contributions of this dissertation are methodological and practical, with the whole adaptable framework, and with the multiple experiments and case studies, which provide insights on successful implementation strategies of ridesharing and carsharing systems that can be very useful to service providers and decision makers.

The main objective of the framework introduced is to present an analysis tool to emerging alternatives of shared systems, which attempt to solve current transportation inefficiencies. These new strategies attempt to reduce the number of vehicles on the roads, which at the same time increase the use of SAVs to fulfill the same transportation needs, impacting the total life of those vehicles. In this research, we present a new framework which includes vehicle usage and cost distributions, a trip optimization ridematching algorithm, an agent based simulation system, a vehicle bookkeeping tool, and a system benefit cost analysis. This framework has been developed to study the interactions of new price-cost-ownership paradigms with traveler usage patterns and system performance in these new mobility systems.

The information and analysis presented is based on information from the US, however, the results would be applicable in any similar scenario, especially considering that shared transportation systems continue to gain wide acceptance in societies all over the world. These systems allow people to travel efficiently without having to own a vehicle. In particular, autonomous vehicles can greatly expand the travel choices of people and incentivize the development of more innovative transportation systems. We can make use of this type of framework and leverage real-time information about people's movements and behavioral choices to make more efficient transportation systems.

An analysis of the current vehicle ownership and trip distributions is presented to support the impacts of shared systems and usage implications. We focus on the different types of vehicles and trips, the odometer and usage of vehicles (mileage associated per trip and in total), the age, and the relationship with the associated current and equivalent estimated miles. The results obtained insist on the importance of considering the mileage of vehicles as a critical variable as they are used more, and their life cycle span is considerably reduced. The age of a vehicle serves to indicate its level of use; however, we find that the mileage associated gives a better indicator of their life cycle and how much longer we could use them. Current and previous studies considering the average of 15,000 miles per year might work for short term scenarios, but better approaches should be developed to consider the rate of use and renovation of vehicles. This gets extremely important in shared mobility studies, where mileage gets more importance as vehicle are used more, and their life cycle span would be considerably reduced. The distributions obtained represent the basis of the vehicle information in the framework.

It is important to consider the necessity of better datasets to simulate more realistic transportation systems, in particular if we try to consider new mobility options. They should include more detailed information of the vehicles, their mileage, and their costs. With this type of information, we would be able to better simulate and analyze new shared mobility systems and improve the current transportation situation. In the time of this dissertation, we have not seen any analysis that properly considers the cost of vehicles as a consequence of their increased usage in these systems. We present properly designed vehicle cost usage functions which assess this situation and are utilized to adapt the objective function of the transportation system, so as to optimize it from the point of view of the vehicles and the associated costs as well, instead of just using the user-side travel times.

Considering the vehicle's usage cost allows us to reduce the number of vehicles needed to serve a demand, which at the same time would increase their mileage. This would in turn reduce the life of the vehicles used, which is a detail that current models do not properly account for. By creating a cost function for each vehicle, we can consider the individual characteristics and update them as they are used. However, this brings new situations in which we go from a centralized optimization system to a more decentralized situation in which we can obtain information from the point of view of the vehicle. By improving the average cost model, we obtain more efficient solutions, which could end in a situation where we could do optimizations individually for each vehicle's operation so that every car optimizes its own trips and usage.

The key aspect of this dissertation is the framework created to analyze new shared mobility systems based on the increase vehicle usage cost. We have introduced and analyzed all the agents and elements from the framework, the information it will use, the ridematching and simulation processes, and the mathematical formulation to optimize the system and analyze the results obtained. We are considering a representative group of different types of vehicles, where we can simulate the mobility of small networks and analyze their increased usage. With that, we can consider initial estimates of their cost and by obtaining their mileage we can obtain how much they cost to the system.

We can also notice that, depending on who is making the decisions and what is his final objective we could have different potential scenarios. We could have the public administration controlling a fleet of SAVs trying to minimize the cost and offering a good mobility option, or private companies trying to minimize the cost and maximize their profit. This framework is prepared to consider many different scenarios and costs, in particular situations derived from a shared mobility provider that matches users from the system, and the use of an autonomous vehicles fleet system. As a result, we have shown the simulation of these vehicles, and the optimization of the transportation system with a new cost function that considers the increased usage of vehicles.

In the benefit/cost analysis we have shown the importance of the extra costs derived from riders wanting to use the system but not being able to be matched to another driver, or in the case of AVs, similar situations where there are not enough vehicles to serve the whole demand. These costs represent a crucial factor in the design of the mobility service as they directly affect the profit of the company in charge. Moreover, a pricing scheme has been presented, along with the interaction elements of the system. This process can be linked to the mobility portfolio cases where we restrict the used modes and their pricing subscription plans, with an improved emphasis on the use of vehicles, and how their impact affects the rest of the elements on the network.

The variety of simulations that are presented provide interesting insights on the behavior of shared systems in different circumstances. This dissertation is focused on the importance of the increased usage of vehicles and how the system can benefit from a vehicle point of view optimization. It envisions the scenarios that will exemplify the importance of considering the changing costs because of the increased mileage of vehicles. We have presented a framework that analyzes the interactions between all the elements to improve the performance of new shared mobility systems. The results presented can potentially lead to efficient design considerations in future practical implementations.

Considering the proper pricing and cost of a system can lead to more adequate rider and driver matching situations and be used to optimize the vehicle fleet size of a service provider, which results in a more efficient transportation system. In a similar thought, adjusting the fleet size to the number of users and consider their costs and profit result of their pricing could lead to more efficient shared systems. These observations have strong policy implications, we could suggest that providing incentives for individuals to participate in sharing systems would give a higher chance of reaching optimal matching rates for sustainable operations.

In terms of mileage per vehicle we observe how the more AVs in the network, the less trips are done with conventional vehicles, and individual usage per vehicle increases. This result reaffirms the idea that ridesharing systems, especially the ones associated with autonomous vehicles, increases their usage in the same time frame, which is better assessed with a vehicle cost usage optimization. AVs are more used individually and in average. For this reason, we have presented a transportation system that allows an easier and better control of their costs and use, especially if we combine the systems with a cost optimization where we can consider the trip cost depending on the vehicles. We have observed how the empty miles per AV initially increases as a result of a low fleet size, and once there are enough vehicles in the network to start optimizing the trips, this value decreases until it reaches the optimal fleet size for vehicle use and profit.

As a base line comparison, we also have shown a shared system where users are matched with the closest AV possible, instead of considering their cost. If we consider the extreme case of having one AV per rider, all of the vehicles are used instead of the conventional cars. The riders will not have to wait for an AV but with the drawback of a much higher cost associated. It is also in this scenario where we see the highest VMT. This is exactly one of the issues of including new ridesharing technologies analyzed in this dissertation. We have just transferred the use of individual vehicles to a service provider without obtaining any benefit. This situation adds extra costs due to the extra empty miles associated to the AVs. It is utterly important to combine new shared mobility systems with a proper cost usage framework, in order to optimize the matching and use of vehicles as presented in this research.

We have seen how initially the monthly cost of AVs would overpass the cost in other scenarios, as we start introducing the adjustment in the cost per mile, the cost of using AVs gets lower than owning a vehicle. This type of approach suggests that mobility subscription service plans of using shared AVs can be more efficient for the mobility and cost less to the user. Hence, a change in the ownership paradigm combined with new shared technologies can shape how we conceive the transportation systems and can generate new types of companies and options. They would be beneficial for the mobility and the society reducing the number of vehicles needed and adjusting the current infrastructures, and also to the users by creating more adjusted and affordable mobility plans and alternatives.

If we only use the information from the 10 by 10 network, we obtain much lower costs. Thus, we can infer that this type of sharing systems might benefit more from smaller networks where the average trips are shorter, rather than big networks where the trips are longer, and the users are more separated. Empty miles would increase a lot, and so will the usage and costs of vehicles, and more resources would be needed to create more depots to park and deploy the AVs to reduce those miles and corresponding costs.

The replacement results from the AV Sharing system indicate that we would be able to drastically reduce the total number of vehicles needed while maintaining a similar level of service. In certain scenarios we have presented that we could use one autonomous vehicle as a substitute of three personal vehicles. Moreover, the results from the benefit/cost analysis show that this type of framework and sharing systems have the potential to give more options to the service providers, in the case they want to make more profit as a private company, or if they want to improve the level of service and having more costs as a public company.

Extra costs such as pollution or parking are not directly considered in this framework, even if they could be easily included with a proper model vehicle usage cost model. However, as we have observed, the number of vehicles used to provide a similar level of service is much lower than the ones with the conventional vehicle use, but those vehicles are more used in the same time frame. Especially with the use of AVs, the importance and implementation of those models would need to be reevaluated in these situations. The emissions associated with the use of AVs is much lower and is usually derived from the fabrication or production of electricity, and not the use of AVs themselves. Also, if the number of vehicles needed is much lower, the parking associated with those vehicles would also be less important, especially considering the use of depots to store them most of the time. These scenarios would not be part of this dissertation, but could be easily implemented with this framework, thus, they would be considered for future work.

Implementing transportation systems has the potential to introduce a much more flexible and less expensive form of shared-mobility in certain networks, which might affect vehicle ownership the way it is known, reducing the number of vehicles in the street and the vehicles owned by people. This dissertation explores the impact of shared autonomous mobility on private vehicle ownership and the transportation infrastructure and makes recommendations on the policy and the behavioral process that might be a key factor in the transition to autonomous technology.

Part of this dissertation has been developed in the context of COVID-19. Data obtained during this period shows a significant change in travel behavior, with many people working from home, thereby resulting in lower vehicle usage. Also, the tendency in vehicle ownership is being reduced in new generations, especially with the rise of TNCs and other alternatives. This behavioral shift incentivizes people even more to opt for flexible transportation systems, instead of undertaking the financial commitment of purchasing a vehicle. However, in the current situation, the type of shared systems might not be fully ready, and the potential impacts in ownership might not be that important. More studies are required to accurately gauge user perception of ridesharing and vehicle ownership.

In conclusion, the research developed a framework for shared systems that is sound in its theoretical foundations and formulations, as well as in the algorithmic implementations, and demonstrated through different case studies and scenarios the possibilities for its use. Shared mobility has already changed the transportation landscape in cites all over the world. Connected, electric, autonomous, and shared vehicles are expected to revolutionize multimodal shared transportation systems even further. In light of these transformations, the future directions of research that we outlined are essential in promoting better planning, engineering, and operations in communities across the United States and the world. It is hoped that this framework will be of use in the future for transforming the current state of urban travel towards a better world with much fewer vehicles and much more sustainable benefits for the people, the goal behind this research effort.

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