THE ATAXI REVOLUTION:
AUTONOMOUS VEHICLE IMPLEMENTATION AND RIDE-SHARING
OPTIMIZATION IN THE UNITED STATES AND CHINA

ANTIGONE HOPE VALEN
ADVISER: ALAIN L. KORNHAUSER

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Antigone Hope Valen
To Mom, without whom nothing in my life would be possible.

And to Dad, who taught me that hard work has no substitute.
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Abstract

Autonomous vehicles (AVs) - cars that can sense their environment and navigate without human input - have been a much discussed and highly debated phenomenon in recent years. While the technology will likely be disruptive, there are significant benefits worth analyzing to paint a full picture of what the world could look like in the near future and how AVs could shape the landscape of transportation. How will urban centers change? How will fundamental attitudes toward transportation shift?

Two of the most advanced countries in the AV arena are the United States and China. U.S. technology companies from Tesla, Uber, Intel and Alphabet as well as their Chinese counterparts Baidu, Tencent, Changan, Didi, and Uisee are all investing heavily in the space. They’re developing technology, partnering with original equipment manufacturers (OEMs), and making a push to get regulations in place and cars on the road as early as possible.

This thesis makes the case for AVs in suitable environments and argues that the technology will cause a permanent shift toward ride-sharing within urban centers. It also evaluates the benefits of implementation and addresses prevailing concerns. The phenomenon can benefit the world in many ways - through the improvement of safety, environment, traffic, and efficiency, among others. Driverless cars have the potential to give the young, old, blind, and disabled enhanced mobility. They can solve problems of congestion, accessibility, and parking. But what are the trade-offs? Jobs will disappear. Pedestrians, bikes, and public transportation could be relegated to the fringe of society. And, on an extreme level, cardiovascular issues, diabetes, and other health problems could increase due to lessened physical activity. AVs will no doubt cause disruption in many corners of society, but they will also bring significant benefits.

This thesis then studies AVs in China, focusing on implementation feasibility, market potential, and obstacles. China and the U.S. are developing similar technologies, but the implementation in each country will differ in terms of type of AV, timeline and path towards mostly or fully autonomous, and the regulations that aim to create autonomous-friendly environments. How will AVs integrate into each country and what advantages does China have in this realm? Quoted herein are business executives, technological experts, and academics stating their opinions on what the future holds.

Finally, this thesis mathematically and programmatically tackles the question of how an autonomous ride-sharing service will be implemented in a realistic setting, using Manhattan as a case study. This is done by analyzing synthesized individual trip data and optimally placing passengers in different capacity “aTaxis” to minimize time and distance traveled, while maximizing average vehicle occupancy (AVO). Constraints are varied to discern the best autonomous taxi network (ATN). What is the optimal ride-sharing system for Manhattan and how will shared autonomous vehicles (SAVs) replace the existing individual car ownership culture?

It is no longer a question of whether AVs will hit the road; it is now a matter of when and how. This thesis sheds light on both matters.
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Chapter 1

Introduction

1.1 Transportation

Transportation - the movement of people and goods by automobiles, trucks, trains, ships, airplanes, and other vehicles - is one of the most important aspects of everyday life. Looked at another way, it is the creation of place and time utility while incurring a cost. People travel to acquire some type of service, be it location, time, comfort, or convenience. Transportation of some sort has been around since the first humans, whether by mammoth, ship, horse, carriage, car, or airplane. While there has been a series of major transportation innovations, none so far has been as important as the individual car. The automobile revolutionized transportation through accessibility and efficiency. Driving augmented the landscape of the industrialized world, creating the rise of and migration to the suburbs by allowing for realistic commutes back and forth from urban centers.

Automobiles, as today’s main form of transportation, have become a dependency for much of the developed world. In Peter Dauvergne’s book, The Shadows of Consumption, he discusses the road to a world dependent on automation and automobiles. He writes:

The history of the automobile shows how, over several generations, as technologies develop and personal incomes rise, societies can become dependent on a consumer product. It also shows how, subject to little governmental control,
This dependency can reorient communities and economies, leaving few to question the costs and risks of the resulting ecological shadows.\[26\]

This presents transportation as a double-edged sword. While transportation brings many advantages that have rendered consumers dependent on its services, there are social, economic, and ecologic consequences of this phenomenon. Due to these undesirable aftereffects, transportation is on the verge of revolution yet again - this time through automation.

Automation in vehicles can be found at many different stages. Currently, many cars have automated systems in place to assist drivers at different levels, including cruise control, automated parking, and emergency break systems. The Society of Automotive Engineers (SAE) defines six levels of vehicle automation, from no automation to full automation, as explained below in Table 1.1. Its definition of the dynamic driving task includes the operational (steering, braking, accelerating, monitoring the vehicle and roadway) and tactical (responding to events, determining when to change lanes, turn, use signals) aspects of the driving task, but excludes the strategic (determining destinations and waypoints) aspect.

There are other ways to define levels of automation, including one by Alain Kornhauser that splits automation into three categories - Automatic Emergency Breaking (AEB), Self-Driving, and Driverless - and are further explained in Table 1.2. This method consolidates SAE’s levels into more distinct categories.

The current autonomous transportation landscape, which will be outlined in depth in the next section, includes certain features of these levels. Many technology companies and traditional original equipment manufacturers (OEMs) have cars on the road with minimal to high levels of automation. Tesla, for example, states that “All Tesla vehicles produced in our factory have the hardware needed for full self-driving capability at a safety level substantially greater than that of a human driver.”\[57\] The prevalence of self-driving systems in all types of cars - not just technology-forward ones like Teslas - is only increasing in the years to come.

Along with the shift to automation, there has also been a push toward ride-sharing. Up to present day, road transportation has, for the most part, been an individualized phe-
Table 1.1: SAE Levels of Automation [50], as of January 2014.

<table>
<thead>
<tr>
<th>Level</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Human Driver Monitors Driving Environment</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>No Automation</td>
<td>Full-time performance by the human driver of all aspects of the <em>dynamic driving task</em>, even when enhanced by warning or intervention systems.</td>
</tr>
<tr>
<td>1</td>
<td>Driver Assistance</td>
<td>Driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration with the expectation that the human driver perform all remaining aspects of the <em>dynamic driving task</em>.</td>
</tr>
<tr>
<td>2</td>
<td>Partial Automation</td>
<td>Driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration with the expectation that the human driver perform all remaining aspects of the <em>dynamic driving task</em>.</td>
</tr>
<tr>
<td></td>
<td><strong>Automated Driving System Monitors Driving Environment</strong></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Conditional Automation</td>
<td>Driving mode-specific performance by automated driving system of all aspects of the <em>dynamic driving task</em> with the expectation that the human driver will respond appropriately to a request to intervene.</td>
</tr>
<tr>
<td>4</td>
<td>High Automation</td>
<td>Driving mode-specific performance by automated driving system of all aspects of the <em>dynamic driving task</em>, even if a human driver does not respond appropriately to a request to intervene.</td>
</tr>
<tr>
<td>5</td>
<td>Full Automation</td>
<td>The full-time performance by an automated driving system of all aspects of the <em>dynamic driving task</em> under all roadway and environmental conditions.</td>
</tr>
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</table>
nomenon. People with sufficient means have owned their own horses, their own carriages, and now their own cars. The option to own one’s means of transport has long existed and has been centered around the individual’s wants and needs. As Dauvergne’s forewarnings have crept up on society, however, there has been a need to innovate and adapt the current methods of travel. These realizations have led to ride-sharing. Whether co-workers car-pooling to work or people switching from UberX to UberPOOL, society is starting to turn toward this more sustainable method of transportation. If the trend continues, it is possible, and even likely that individual car ownership will become obsolete due to the various benefits and cost savings of well-designed autonomous taxi and ride-sharing services. Owning one’s own fully self-driving car will become too expensive for the majority of society, meaning that the earliest and most likely adopters of AVs will be ride-sharing companies. This shift will be represented by autonomous taxi networks (ATNs).

Brownell and Kornhauser define ATNs as consisting of fully autonomous, interconnected, and constantly communicating “aTaxis” that pick up passengers according to traveler demand and drop them at their requested destination. They do not run on a schedule and are instead “demand-responsive,” or deployed according to individualized passenger requests. There are two types of ATNs: one modeled off Personal Rapid Transit (PRT) systems and one called Smart Para-Transit (SPT). Kornhauser describes a PRT-based ATN as a system that assumes passengers will walk to and from their closest aTaxi “stand,” using a

---

### Table 1.2: Kornhauser’s Three Levels of Automation

<table>
<thead>
<tr>
<th>Level</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AEB</td>
<td>Detection of an impending forward crash with another vehicle in time to avoid or mitigate the crash.</td>
</tr>
<tr>
<td>2</td>
<td>Self-Driving</td>
<td>Highly automated driving system able to perform all aspects of the driving task. Uses technologies such as GPS, LiDAR, lane-centering, and autonomous collision avoidance system (ACAS).</td>
</tr>
<tr>
<td>3</td>
<td>Driverless</td>
<td>The full-time performance by an automated driving system with no human intervention.</td>
</tr>
</tbody>
</table>
distance constraint of roughly 0.35 miles at most. The vehicles will pick up one or more passenger(s) depending on whether his or her origin and destination matches the others' “pixel,” or small area of land that categorizes demand location. Mark Gorton explains the alternative type of network - an SPT - where people are picked up at a “central transit point” and the aTaxi may make stops at various other points along the way. Instead of, for example, two passengers having to walk (at most) 0.7 miles to a PRT ATN station, the passengers would be picked up at a very nearby central transit point, make stops along the way, and reach their respective destination central transit points. Figure 1.1 shows a representation of Gorton’s SPT system.

![Figure 1.1: Representation of Mark Gorton’s SPT System](image)

What are the effects of a shift toward aTaxi services? Parking lots and garages will be repurposed and perhaps people - who won’t want to have to walk more than five minutes to the nearest aTaxi stand or pickup location - may start living closer together to minimize travel time. What direction is transportation heading? The National Highway Traffic Safety Administration (NHTSA) states that “the development of advanced automated vehicle safety technologies, including fully self-driving cars, may prove to be the greatest personal transportation revolution since the popularization of the personal automobile nearly
a century ago.”[46] This revolution will drive individual transportation permanently toward ride-sharing.

1.2 Current Landscape

The current AV and driverless technology landscape is active and widespread. From companies like large technology firms and traditional OEMs to small start-ups from a variety of different countries and industries, everyone seems to want a piece of the action. AVs are expected to hit the market by 2021, and BCG anticipates it will take 15-20 years - or between 2035 and 2040 - for them to reach a global market-penetration rate of about 25 percent.[43] This indicates that many companies are well underway in developing and testing these cars. As of late 2016, AVs existed on the road in cities across the world, shown below in Figure 1.2.

![Map of Autonomous Vehicles on Public Roads Worldwide](image)

Figure 1.2: Map of Autonomous Vehicles on Public Roads Worldwide [62]

From Mountain View, California to Fujisawa, Japan, AVs are being tested on public roads. In the United States and China, especially, companies have made a vigorous effort to be at the forefront of the AV revolution, shown by a significant amount of merger and acquisition (M&A) activity surrounding early and late-stage AV-related start-ups, as companies try to acquire the best technologies and access to different markets.
1.2.1 Corporate Players and Progress

United States

When thinking about companies involved in AV development and technology, Tesla immediately comes to mind. It has burst onto the AV scene over the past few years, equipping all its models with “Autopilot,” which it deems safer than the human driver. In fall 2016, Tesla updated Autopilot with improved digital mapping. Cars that have the new software, known as Version 8, note the positions of road signs, bridges and other objects, and send the data to a centralized database that other Tesla vehicles can draw on to make safe driving decisions. Tesla calls this “fleet learning.” Despite its impressive progress, however, Tesla’s main news story in the past year has been Autopilot’s fatal crash. Joshua Brown, the passenger, died in Florida when his 2015 Tesla Model S was operating under control of the electric car’s Autopilot system. According to the *New York Times*, as the car was traveling on a state highway at seventy-four miles per hour, a white tractor-trailer was crossing the road, but Autopilot’s sensors had trouble recognizing it against a bright sky. Tesla has said Autopilot may have thought the truck was an overpass. An investigation of the crash by the NHTSA found no safety defect in Tesla’s Autopilot technology. It added, however, that Tesla needed to be cautious in its marketing and advertising not to overstate the capabilities of Autopilot, a semiautonomous system that requires drivers to keep their eyes on the road and hands on the steering wheel. Many have expressed concern that Tesla’s bullishness in the realm of AV rollouts has made it more difficult for society and the government to trust the technology on the whole. Still, many other companies are making active pushes and attacking the market from various angles.

Google, another one of the most common names on the AV front, started developing AVs in 2009 and has kept its progress relatively under the radar. The company has now tested self-driving vehicles over 2 million miles. Alphabet, Google’s parent company, recently spun off its AV division into what is called Waymo, headed by Jon Krafcik. The company is working on testing vehicles, although some say Google has lost its “first-mover advantage” to competitors given that it hasn’t yet introduced an AV service to the public. One of these such competitors is Uber. Launched in 2010, Uber has a valuation of close to $69
billion and operates in over 100 U.S. cities and many more across the globe. Uber recently acquired the self-driving car company Otto and launched fleets of self-driving vehicles in Pennsylvania, California, and Arizona.

With the rise of new technology and competition to get there first unfortunately brings conflict and lawsuits. Alphabet and Waymo have recently sued Uber and Otto over theft of self-driving technology; Waymo claims that Otto is using Waymo’s LiDAR technology, a crucial component of AV development. Uber has also encountered recent obstacles relating to their autonomous fleets. In March 2017, one of its self-driving vehicles in Arizona crashed, causing Uber to suspend its AV pilot program. Moreover, the fleets had been underperforming. A company report on how their self-driving fleets have functioned was leaked, showing poor results. During one week in early March 2017, the company’s 43 active cars drove 20,354 miles autonomously according to the documents and as shown below in Figure 1.3. Vehicle miles traveled (VMT) had been increasing, but the results do not show linear progress.

Figure 1.3: Total Number of Miles Driven by Uber’s Autonomous Vehicles per Week  

According to Uber’s report, the company uses three metrics to judge the progress of their fleets:
• *miles per intervention*: the average number of miles a car drives itself before a driver has to take over for any reason

• *miles per critical intervention*: when a driver has to avoid causing harm, such as hitting pedestrians or causing material property damage

• *miles per bad experience*: events such as jerky motions or hard braking, which are more likely to cause discomfort than damage

Figures 1.4-1.6 below show the graphical results for each metric.

![Figure 1.4: Uber’s Miles per Intervention](image1)

![Figure 1.5: Uber’s Miles per Critical Intervention](image2)

While there have been some minor improvements, the overall message is that Uber’s cars have not necessarily become safer or more pleasurable. The “first-mover advantage” seems to be more of a disadvantage at this point, due to imperfect technology for everyday
Successfully creating self-driving technology has become a crucial factor to Uber’s profitability, given that it allows Uber to generate higher sales per ride since fares aren’t being split with drivers. Hopefully, Uber will have the time and credibility to improve its fleets and current reputation, but being one of the first companies in the spotlight is, as also shown by Tesla, not necessarily an enviable position.

Aside from the U.S. technology firms, many OEMs have made a large push in the autonomous direction as well. Most traditional car companies know that their future will likely depend on their ability to adapt and provide to the AV market. Ford, for example, announced that its goal is to produce its own self-driving car by 2021. In February 2017, the company announced investing $1 billion over five years in an AV technology start-up called Argo AI. General Motors similarly acquired Cruise Automation for $1 billion in early 2016. Audi presented its highly autonomous A7 model, which has highway-driving capability, at the 2015 Consumer Electronics Show in Las Vegas. The car drove itself from San Francisco to the show - a distance of 550 miles. Volvo launched its “Drive Me” initiative in both Sweden and China, where 100 self-driving cars navigate public roadways in everyday conditions. The shift to autonomy is important for many OEMs, which know they need to partner with, invest in, and acquire companies moving in the same direction.

Two other big names in the AV market are Intel and NVIDIA, both of which are developing self-driving technologies for cars. According to an article by NASDAQ, the Intel Go computer and NVIDIA Drive PX 2 are designed to help cars detect pedestrians,
objects, lanes, respond to traffic signals, and more. Currently, BMW is testing the Intel solution while Tesla is testing the NVIDIA solution. The artificial intelligence platform used by Baidu, a Chinese web services company, also combines its cloud platform with NVIDIA self-driving technology to deliver features like HD maps, vehicle control, and automated parking for the Chinese market. NVIDIA has a lead in the machine learning segment and its automotive chips are already in millions of cars from a number of suppliers, which in combination gives it an edge in the automated car segment. Intel has been on the move in terms of M&A activity, collaborating with Mobileye and announcing that it will buy the Israeli supplier of self-driving technology (camera and laser-based sensors) for $15 billion. Mobileye currently sells its technology to twenty-seven automakers across the world, so the combination will be highly advantageous for Intel. Intel plans to headquarter its autonomous driving operations in Israel, which, according to Mobileye co-founder and Chief Technology Officer Amnon Shashua, gives the country an opportunity “to lead how these autonomous vehicles go out on their own, interact with cities, interact with government agencies and really set the standards for how this gets implemented into the world.” In November, the two companies also announced a self-driving partnership with vehicle technology supplier Delphi Automotive, setting the stage for a global AV powerhouse in the coming years.

China

China’s corporate landscape is similar to that of the U.S. in that the companies involved in AV development span different sizes and industries. There are technology giants like Baidu, start-ups like Uisee, traditional auto companies like Changan, and ride-sharing companies like Didi Chuxing. Baidu in China is somewhat similar to Google in that it is a web services company that has the capacity for innovation across many different technologies. Baidu has a large AV division and has plans to commercialize its self-driving vehicles by 2018, which will begin with several trials in ten different Chinese cities. The company has been working with BYD Co., China’s leading electric car maker, to equip what they call AutoBrain systems: a software package that utilizes artificial intelligence software and deep learning models. This is the core of Baidu’s autonomous driving technology. As it
stands, Baidu straddles the line between two interesting possibilities: one could see Baidu-branded AVs on the road or they could instead become a supplier of AutoBrain to separate assemblers. Competitors of Baidu, Tencent and Alibaba, have also been investing in the space. In late 2016, Tencent, a Chinese Internet giant best known for its WeChat messaging app, announced a 10 percent stake in a Netherlands-based digital mapping company HERE Global BV, controlled by automakers Audi, BMW, and Daimler. The company also recently took a 5 percent stake in Tesla. Alibaba, China’s e-commerce titan, has similarly collaborated with China’s SAIC Motor for the development of AVs. As it stands, Tencent is a small player when it comes to mapping technology, as its maps are only used by about eight million people, compared to a combined 200 million for Baidu and Alibaba. With continued investment in AV-technology companies, however, large technology firms will continue to jostle for leadership in the self-driving market.

Changan, Ford’s Chinese partner, is an example of an OEM that has adapted to the shifting tide toward AVs. According to a press report on its website, on April 12, 2016 Changan’s own Raeton sedan began an autonomous demonstration drive from their General Research Institute in Chongqing to Beijing. The release states,

Upon its arrival in Beijing on April 17, 2016, this autonomous vehicle will have covered over 2,000 km. This autonomous road demonstration will make Changan the first Chinese automaker to have developed and tested a long distance autonomous driving vehicle. This Raeton test vehicle demonstrates Changan’s strength and leadership among Chinese OEMs in developing autonomous technology. This project’s success signifies a technical leap from the traditional automobile to the smart automobile.

Echoed in this announcement is an emphasis that making the switch to autonomy is crucial to future success. Changan’s Li Shufu recently stated a self-driving model should be on the market in two to three years, with the automaker spending five billion yuan ($773 million) to further the technology by 2020. It is also in talks with Baidu to develop automated driving technology, marking another potential partnership and further consolidation within the market.
Another company with significant market potential in China is a start-up called Uisee. Uisee, which stands for Utilization, Indiscriminate, Safety, Efficiency and Environment, started with Gansha Wu (a former engineering manager at Intel), Jiang Yan (a mechanical expert from the Beijing Institute of Technology), and a former Google employee. Its focus is on developing a self-driving vehicle that aids the human driver instead of replaces it. The company combines all aspects of the self-driving platform - from hardware to software, deep learning, and beyond. Uisee is an example of the growing start-up culture in China and should have a foothold in the market going forward.

China’s main ride-sharing company, Didi Chuxing or “Didi,” has a valuation of $35 billion and executes over fourteen million trips a day in 400 Chinese cities, making it the largest ride-sharing service in the world. Uber sold its China business operation to the firm, making Didi a promising contender for the future of autonomous ride-sharing in China. Apple also recently took a $1 billion stake in the company, with CEO Tim Cook saying, “we are making the investment for a number of strategic reasons, including a chance to learn more about certain segments of the China market.” Interestingly, Didi just opened a self-driving lab in Mountain View, California near Apple’s headquarters. While Apple is developing a self-driving car under the name Project Titan, reports have suggested that it will be turning its focus to technology’s software side. According to the Wall Street Journal, Apple secured a permit for autonomous vehicle testing in California on April 14, 2017. While Apple has operated mostly under a veil of secrecy, it certainly has a strong position in the race to autonomy. Given this news, it will be intriguing to see how Apple and Didi collaborate in the coming years.

The corporate landscape is widespread and only growing, as new start-ups crop up and more established companies invest in AV development. The path toward autonomy has been paved, but it will still take a lot of effort and money to get there. BCG estimates that to bring the entire suite of AV features to market, OEMs and suppliers will have to make significant research and development (R&D) investments - upwards of $1 billion per OEM - over the next decade. This will be used to further develop sensors, processing technology, and integration software as well as to perform testing, validation, prototype design, and pilots.
1.2.2 Regulatory Environment

The current regulatory environment in the AV realm varies across country and state. As of February 2017 in the United States, eleven states and Washington D.C. had passed AV legislation, as illustrated in Figure 1.7 below. Regulations range from establishing a Joint Legislative Committee to study self-driving vehicles in Alabama to authorizing transportation authorities to conduct a pilot project for testing AVs that are not equipped with a steering wheel, a brake pedal, an accelerator, or an operator inside the vehicle in California. In January 2016, U.S. Transportation Secretary Anthony Foxx unveiled new policy that updated the NHTSA’s 2013 preliminary policy statement on AVs and made a commitment of nearly $4 billion over the next ten years to accelerate the development and adoption of safe vehicle automation. The new policy is designed to facilitate and encourage development and deployment of technologies with the potential to save lives. Legislation topics span various angles, including insurance and liability, operation on public roads, infrastructure and connected vehicles, privacy of collected vehicle data, operator requirements, vehicle testing, and cybersecurity of vehicle. Companies will have to share extensive amounts of data with the federal government in order to test and implement AVs.
The challenge that the U.S. will face in terms of AV regulation is the fragmented nature of state governments and achieving uniform guidelines across these boundaries. As it stands, there are few agreed-upon technical standards and differing degrees of regulation between state government levels. According to Chris Urmson, the former head of Google’s self driving car project:

In the past two years, twenty-three states have introduced fifty-three pieces of legislation that affect self-driving cars - all of which include different approaches and concepts....Although all [passed] were intended to assist the development of the technology in the state - none of those laws feature common definitions, licensing structures or sets of expectations for what manufacturers should be doing. [60]

Companies developing cars for the U.S. are going to face difficulties if the cars they make for California will not be able to operate in, say, Florida or New York.

In China, because of one-party rule, regulation has the potential to be much more cohesive. There still, however, needs to be a national framework for dealing with AV policy. Right now there are about ten ministries responsible for the supervision of some aspect of AVs, from the Ministry of Public Security and Ministry of Transport to the Ministry of Industry and Information Technology and National Administration of Surveying, Mapping, and Geo-Information. [62] As mentioned in a Brookings report relating to Chinese regulation:

The government also needs to invest in highway infrastructure development for autonomous vehicles, eliminate the current national prohibition on road testing, reduce restrictions on road mapping so that car makers and software designers can learn from experimental trials, develop technical standards for autonomous vehicles, address legal liability in cases of accidents, and improve awareness of autonomous vehicles. [62]

While this seems like a lot to accomplish, China’s advantage is that its regulatory processes for AVs mostly operate at the national level. As will be discussed later, China’s motivation to adopt AVs should help the country overcome the current short-term regulatory obstacles.
1.3 Manhattan aTaxi Service Optimization

Aside from examining the current landscape of and making the case for AVs and ride-sharing, this thesis also proposes a practical solution to the autonomous ride-sharing service implementation problem in Manhattan (FIPS Code 36061). It aims to categorize the demand of person trips taken in Manhattan in order to simulate how an autonomous taxi service can serve such demand. To do this, it is necessary to understand the spacial and temporal distributions of demand for transportation services in Manhattan. By studying demand on an individual level, this allows for a comprehensive solution on how to supply these types of ride-sharing autonomous services.

1.3.1 Trip Data

Princeton student Kyle Marocchini’s simulated trip data generated for his independent work titled “A National Hybrid Activity/Agent-Based Demand Model to Characterize the Mobility of the United States” was used in this problem to determine the trip demand in Manhattan. In his paper, Marocchini introduces a hybrid of activity- and agent-based modelling to generate individual demand nationwide. His stated objective of the model presented is to generate a synthetic listing that details the personal trips taken by all residents of the U.S. Some key terms here are:

- **Activity-Based Modelling**: realizing transportation as a demand deriving from people’s needs and desires to participate in activities

- **Agent-Based Modelling**: realizing transportation as a demand by incorporating the complexity of human behavior using “agents” that are autonomous and interactive

In his hybrid model, Marocchini adopts a trip-schedule framework from the Activity-based model and a focus on individual behavior from the Agent-based model. Individuals are aggregated at a household level and all trip tours begin and end at home, while residents are grouped by households. The temporal unit used is the U.S. workday, assuming that weekdays are identically distributed. Marocchini hence generates a synthetic populace,
assigning workplace, school, activity patterns, trip destination, and arrival and departure times to individuals. He finally pixelizes the demand for the analysis of ATNs. In Marocchini’s original data the pixel side-length, $d_s$, is equal to 0.5 miles, but for the purposes of this problem in Manhattan, the data will be repixelized into smaller units ($d_s = 0.3$) in Chapter Five.

After taking these steps and pixelizing the whole nation, Marocchini’s data shows state-by-state and county-by-county individual trips that can be used for the analysis of an ATN. For the purposes of this problem, only trips with the origin and destination in Manhattan (FIPS code 36061) are used to obtain a contiguous area. Manhattan is a useful case study for an ATN given its compactness and organization as a city. The aTaxi stands or “central transit points” can be convenient and close together. Brownell and Kornhauser state that one of the necessities an ATN must provide is a “solution to the congestion problem.”\cite{19}

The congestion in Manhattan is notorious, so the city should welcome a ride-sharing solution.

1.3.2 Ride-Sharing Impact on Trips

Using the individual person-trip data, it is possible to then construct a program that places people in an aTaxi ride-sharing system based on certain constraints. The algorithm for this problem is modeled off the work of Bill Van Cleve, August Kiles, and Tianay Zeigler’s analysis in “Nationwide AVO,” with some significant alterations.\cite{32} This aTaxi service is set up as the previously discussed SPT system, where the aTaxi makes various stops at pixels along the way to its final destination, as opposed to a PRT system that only makes one stop at the origin and destination. The first important constraint in designing this type of service is that Common Destinations (CD) = $x$, which means any given aTaxi will stop no more than $x$ times in total after picking up passengers. Secondly, Departure Delay (DD) is assumed to be $y$ seconds. As soon as a passenger gets into the aTaxi, it will wait no more than $y$ seconds for other passengers to board before departing. A maximum circuity constraint of $z$ is also implemented so that no passenger will travel more than $(1 + z)\%$ of the distance he or she would if going in a straight line from origin to destination. Finally, different passenger constraints are assumed. These constraints are
varied to analyze capacity’s affect on trips, VMT, average vehicle occupancy (AVO), trip length, and trip duration.

The program outputs a file of aTaxi trips with information on taxi number, origin and destination pixels, riders at time of departure, number of riders who deboard at each stop, person trip miles served, aTaxi vehicle miles driven, arrival time, and AVO. With this information, it’s possible to then analyze the effects of an aTaxi system in Manhattan. How do different constraints affect VMT and trip length distributions? What’s the AVO comparison between the current system and different capacity aTaxis? The AVO, defined as the benefits of service over cost, in an aTaxi network should be higher than in the current individual car ownership system. What are the cost per passenger mile implications? These questions will all be examined in Chapter Five. Additionally, after finding the optimal service for Manhattan, aTaxi stands are placed on a map at the centroid of each pickup pixel. Through the analysis of latitude and longitude pairs it is possible to visualize the trip density at each stand.
Chapter 2

Literature Review

Although automation in traditional vehicles is a relatively new field of study, there have been many articles, reports, and papers written on the future of autonomous driving, covering all different aspects of the issue from technological developments, implementation, and societal acceptance, to the reshaping of urban centers. Below is a summary of the existing literature and analysis done on autonomous vehicles, broken down by subject category. The overall tone is positive, if not hopeful, implying the inevitability of AVs hitting the road, but not without some serious obstacles that must be heeded with careful attention and planning.

2.1 Technology Overview

AVs require a combination of hardware and software to operate. This includes artificial intelligence, high definition maps, and deep learning. The more specific technologies that fall under these classifications are automated vehicle guidance and braking, lane-changing systems, use of cameras and sensors for collision avoidance, artificial intelligence to analyze information in real-time, and high-performance computing and deep learning systems to adapt to new circumstances through 3D maps. Figure 2.1 contains a graphic of a self-driving vehicle with some of the major technologies explained.

This graphic shows most of the hardware necessary for AVs. Cameras, GPS, sensors, an ECU, and connectivity to maps and software are crucial for operation. It also shows the
prices of each component. GPS and LiDAR will be the most expensive, while sensors are relatively cheap.

2.1.1 LiDAR

A key piece of hardware needed for AVs are light detection and ranging systems, otherwise known as LiDARs. These systems are necessary for navigation and collision avoidance. This sensor technology combines light and radar instruments mounted on top of vehicles, and uses imaging in a 360-degree environment from a radar and light beams to measure the speed and distance of its surroundings. According to a BCG report, their collection techniques make them capable of producing extremely high accuracies and point densities, thus permitting the development of precise, realistic, three-dimensional representations of objects. Sensors are also placed on the front, sides, and back of vehicles to keep cars in their own lane, avoid other vehicles, and apply brakes and steering when needed. There are many LiDAR systems already existing, but they need to be much further developed and have their cost scaled down before universal adoption by OEMs and other companies. The costs of LiDAR systems range from $90 for a single-beam unit used in advanced driver

Figure 2.1: Technology Requirements for Autonomous Vehicles [43]
assistance systems (ADAS) applications to $8,000 for an eight-beam array that is better suited to AV applications.[43]

2.1.2 High Definition Maps

High Definition (HD) maps are crucial to autonomous driving, as they provide the capability for navigation and vehicle placement on roads. While traditional maps are redrawn usually once every three months, highway and other maps for AVs need to be updated constantly due to construction and other changes. HD maps are much more precise than GPS coordinates, which are only accurate within five to ten meters. Baidu, for example, has HD maps for China that are accurate within five to twenty centimeters (or about two to eight inches). According to an interview Brookings conducted with a Baidu employee, the company uses ten surveying cars for high definition maps and uses the centimeter-level HD map for its driverless car.[62] The maps include detailed information on traffic signs, lane markings, curbs, over- and underpasses, poles, barriers, etc. This information is then geo-coded so that navigational systems can match features, objects, and road contours to precise positions for car guidance. HD maps offer AVs the capacity to analyze information and learn from changing circumstances.

2.2 Market Penetration and Timing

Looking at the implementation of AVs, there are various estimates as to when and how they will penetrate the market. BCG’s “Revolution in the Driver’s Seat: The Road to Autonomous Vehicles” report states that AVs will emerge in the premium segment of the market first, sold to consumers who are willing to pay more than $5,000 for AV features. These consumers are said to represent up to 20 percent of the addressable market. Extrapolating from price estimates and willingness to pay, they conclude that the combined market for partially and fully autonomous vehicles will develop gradually until it reaches roughly 25 percent of new vehicle sales. This, they believe, will allow for the introduction of fully autonomous vehicles by close to 2025. Figure 2.2 shows that demand meets market
penetration at around 26 percent for partially autonomous vehicles and 27 percent for fully autonomous vehicles.

![Figure 2.2: OEM Market Penetration Rate](image)

The graph in Figure 2.3 below shows that in the first ten years AV features may be able to penetrate 7 to 13 percent of the market according to historical trends. This rate of penetration aligns with the previous penetration rate of cruise control in 1967, which only slowly won market acceptance in the first five to eight years after its introduction and took an additional ten years to achieve 25 percent adoption. Adapted cruise control (ACC)
was introduced in 2006 and has achieved about 6 percent penetration in U.S. and global markets after nine years.\[43\]

This is most likely a conservative estimate, given that consumers will probably be more eager to acquire autonomous features than ACC but the higher prices of autonomous features may keep penetration in line with these estimates. The BCG report also projects that if ATNs are established in cities across the globe then the penetration of fully autonomous vehicles would increase from 12 percent in 2035 to 23 percent by 2040. As with all of these projections, of course, implementation rests heavily on regulation and other external factors.

Another paper, titled “Market Penetration Model for Autonomous Vehicles on the Basis of Earlier Technology Adoption Experience,” uses generalized Bass diffusion models based on data from previous technologies, including sales and price data on conventional automobiles and hybrid electric vehicles, as well as the usage of internet and cell phones to estimate the adoption curve.\[35\] Lavansi, et al. state that the reason for studying internet and cell phone usage is that they are two revolutionary forces in the history of communications - a role they believe AVs will play in the automobile industry. Bass diffusion models assume adopters of a new innovation are influenced by either mass media or word of mouth. People influenced by mass media are deemed “innovators,” while those influenced by word of mouth are called “imitators.” In the realm of AVs, the diffusion models can be categorized into two groups: conventional (i.e. Bass) or Stated Preference (SP) surveys. They present the conventional analysis in their paper.

Lavansi, et al.’s results assume the market size for AVs is close to 87 million vehicles, based on household data. The paper states that with 115,610,216 households and given that AV technology will significantly reduce vehicle ownership, then 87 million is a decent estimate for the AV market. Figure 2.4 below illustrates their forecasted market penetration curve for AVs. They assume that AV sales start at year 2025, with 1.3 million vehicles sold within five years and an increase to 36 million in another ten years. Their curve shows that the market will be saturated in 2059, when approximately 87 million AVs have been sold. Lavansi, et al. perform different sensitivity analyses surrounding their forecast, including
one on additional costs of AVs and how that affects predicted sales shown below in Figure 2.5.

These results suggest that the adoption curve doesn’t depend heavily on the additional cost of AV technologies. Market size, which depends on how many households will purchase individual AVs, will have a much larger effect on the adoption curve. They conclude, assuming a 75% market size and availability starting in 2025, that saturation may occur approximately thirty-five years afterwards.

Both papers take the approach of looking at historical trends of similar technologies to study market penetration and timing of AVs. Yet while both BCG and Lavansi, et al.
assume that the introduction of AV sales will start in 2025, Lavansi, et al. conclude that market saturation will occur in 2059 whereas BCG concludes, more conservatively, that there will only be 23% penetration by 2040.

2.3 Societal Acceptance

Societal acceptance is a less mathematically or technologically controlled obstacle than the others. The front page of October 2016’s *New York Magazine* cover shows a picture of a stretching highway, with retro cars and people. The cover in Figure 2.6 below centers on one car, in which four passengers, including the “driver,” have their backs to the road and are intently focusing on a game of dominos in between them. In bright red letters across the scene reads, “Is the Self-Driving Car Un-American?”.

![New York Magazine Self-Driving Car Cover](image)

Figure 2.6: *New York Magazine* Self-Driving Car Cover [42]

The main article, written by Robert Moor, debates the advent of the self-driving car. Moor first presents what personally driving a car means to Americans - basically an “en-shrine[ment]” of an “old-fashioned idea - freedom.” He states ominously the effect of the self-driving phenomenon: “Our republic of drivers is poised to become a nation of passengers.” He poses the questions of existentialism (will we become more or less frustrated not in control of the wheel during a traffic jam?), luxury cars (will people still splurge on fast,
expensive sports cars?), and cultural impact (what happens to the cinematic car chase? The hackneyed country song?). The thrill of obtaining a drivers license at sixteen will become nonexistent. There are certainly things to lose, both materially, like jobs, and existentially, like the concept of freedom.

The article takes a turn, however, when Moor talks about the recent shift to acceptance of autonomy. With unbearable traffic and congestion, escalating rates of crashes, and the realistic monotony of driving, the current generation is more amenable to giving way to self-driving cars than older generations. Moor goes on to describe how the very people against self-driving cars - mostly rural people who live outside city limits - have the most to benefit from their implementation. Given their distance from many destinations, they spend the most hours in vehicles, resulting in wasted time and increased probability of crashes. While he takes more of a cautious tone on the phenomenon, his is still one of inevitability.

A report published by KPMG, called “Self-Driving Cars: The Next Revolution,” states that the tradeoff of recapturing the time and energy spent driving will outweigh societal reservation, and that self-driving vehicles will inevitably integrate into society. It writes:

The marketplace will not merely accept self-driving vehicles; it will be the engine pulling the industry forward. Consumers are eager for new mobility alternatives that would allow them to stay connected and recapture the time and psychic energy they squander in traffic jams and defensive driving.

This is a common argument amongst many: the time saved by not driving, allowing one to accomplish tasks, relax, play games, and catch up with friends and family, is a draw too attractive for society to pass up. The report also mentions that the average American commuter spends 250 hours a year behind the wheel and “whether the value of that time is measured in lost productivity, lost time pursuing other interests, or lost serenity, the cost is high.” Today, those commuters inch along during rush hour traffic; they drive in circles around city streets looking for parking spaces; and, according to a report published by the MIT Media Lab, “In congested urban areas, about 40 percent of total gasoline use is in cars looking for parking.” It seems that lowering these costs, whether they be time, gas, or money, will sway those cautious about AVs.
BCG’s “Revolution in the Driver’s Seat: The Road to Autonomous Vehicles” conducted a study in 2014 that measured U.S. consumers’ willingness to buy a partially or fully autonomous vehicle. It surveyed more than 1,500 U.S. consumers who had recently bought a car or intended to buy one soon. Compared with other studies, its results came out largely positive: about 55 percent of respondents said they would consider buying a partially self-driving car, and 44 percent a fully autonomous vehicle. The results are shown below in Figure 2.7.

Figure 2.7: U.S. Consumers’ Willingness to Buy Autonomous Vehicles

Another study done by Schoettle and Sivak of the University of Michigan surveys respondents from the U.S., U.K., and Australia. There were 501 total respondents from the U.S. and they were said to be representative of the population as a whole. Its results paint a more cautious picture of societal acceptance. Figure 2.8 below shows that respondents believe that most of the benefits of self-driving vehicles are likely to be fulfilled. Respondents believe in a reduced number and severity of crashes, improved emergency responses, lower vehicle emissions, better fuel economy, and lower insurance rates. They are skeptical, however, about less congestion and shorter travel times. While not discounting the many benefits of AVs, however, respondents are still “very concerned” about riding in Level 4 AVs, as shown below in Figure 2.9.
There are many different surveys on societal acceptance, some that paint a hopeful picture and some a more cautious one. Overall, people seem to believe in many of the benefits that AVs can bring but are still concerned about liability, data privacy, system performance, and interacting with non-AVs such as conventional vehicles, bikers, and pedestrians.

### 2.4 Impact on Landscape and Urban Centers

Much debate surrounds how AVs will reshape the urban landscape. Moor, in his *New York Magazine* article, mentions that perhaps cars will fill a less vital role in our future lives, causing the lessening of suburbs and compactness of cities. He writes, “Or perhaps,
following a great tidal shift in our values, the sprawling suburbs will wither and cars will be relegated to a minor role, as people decide they would rather walk and ride bikes through human-scale towns and dense, effervescent ... cities.” Another article asserts that AVs could induce increased urban sprawl because people will be more prepared to drive greater distances with faster, more efficient travel. There are compelling arguments for both sides, but even within cities there will be significant changes to infrastructure and urban landscape.

An article in the New York Times, titled “Disruptions: How Driverless Cars Could Reshape Cities,” discusses the potential impacts on urban centers: many fewer parking lots, traffic lights, and parking tickets. Once AVs are able to communicate with each other and interact with smart infrastructure, there will be no need for traffic lights, stop signs, speed bumps, or even speed limits. Narrower streets could become commonplace given that parking spots aren’t necessary. The air will be cleaner. Roads will run much closer together, increasing capacity on city streets and highways. A study suggested that AVs could increase road capacity anywhere from 43% (using sensors only) to 273% (using sensors and interacting with other AVs). Highways could have smaller corner radii for exits and entries as well as shorter merge and diverge tapers.

Parking space will be one of the most obvious changes within cities, both in terms of garages and on the street. The aforementioned New York Times article cites that as much as one-third of the land in some cities is devoted to parking, leading to necessary repurposing of that space once parking spots become obsolete. More homes, offices, and retailers will take up that parking allocation and thus perhaps real estate prices will fall. Carlo Ratti, a professor of the practice of urban technologies at MIT and chair of the World Economic Forum Global Agenda Council on the Future of Cities, wrote an article called “Cities Should Take Back Their Parking Spaces.” He writes that individually-owned cars are parked, on average, 95% of the time and that one ride-sharing car can remove over ten privately owned cars from the street. Ratti cites Paris as one of the early adopters of ride-sharing, and says the city has already removed more than 20,000 private cars from the road. Collective cars demand far less parking real estate, given that they can remain on the go. Initial simulations by the MIT Senseable City Lab show that the need for parking spaces
in urban areas will decrease by up to 70 percent. On-street parking could be reallocated
to other modes of transportation like cycling, walking, or mass transit. Vacant lots could
be populated with green areas or public amenities. The amount of space freed up will have
multiple possibilities for transformation.

Aside from physical infrastructure, the data platforms and inter-connectivity that come
with ATNs will have large impacts on urban centers. Hani Mahmassani’s “Autonomous
Vehicles and Connected Vehicle Systems: Flow and Operations Considerations” introduces
the concept of “Smart Cities.” At the level of an urban area, the data and systems
integration envisioned under an Internet of Things (IoT) results in so-called “smart cities,”
where a web of connected sensors of all types along with shared data platforms enable
efficiencies across urban services in different sectors. Urban infrastructure will build around
the AV network. Connected cities with shared data platforms and intelligent processes
that leverage the data offer opportunities for end users, system operators, and managers,
as well as potential services by third parties. For connected traffic systems, the mission-
critical nature of both the telecommunication and the control systems required to maintain
safe operation calls for levels of sophisticated coordination that aren’t typical in existing
operations.

It remains to be seen how ATNs will impact the landscape and urban centers, but it
will include both infrastructural and inter-connectivity adaptations. It is difficult to map
out how exactly inner cities will change in the advent of a ride-sharing system replacing
individual vehicle ownership, but it is undeniable that cities will become much “smarter,”
with better infrastructure that is connected to the vehicles traveling within them.

2.5 aTaxi Implementation

There has been limited analysis done on actual ATN implementation aside from that
of Alain Kornhauser and Chris Brownell’s “A Driverless Alternative: Fleet Size and Cost
Requirements for a Statewide Autonomous Taxi Network in New Jersey.” Their report
analyzes the implementation of an autonomous ride-sharing service in the state of New
Jersey. It comparatively studies the two different kinds of ATNs: PRT and SPT. It uses
2012-generated trip data to model demand and concludes that both types of ATNs outperform the individually owned and operated car system. Ultimately, their results show that an SPT-based model is a more economically viable implementation than a PRT-designed one. The report then looks at the fleet requirements per half hour of the day to determine the minimum fleet size needed under an instantaneous repositioning method. The SPT implementation requires a fleet size between 1.6 and 2.8 million 6-passenger vehicles to meet the state's travel demand in its entirety at a cost of $16.30 to $23.50 per person per day. Figure 2.10 below illustrates the fleet size requirements throughout the day.

![SPT Model ATN Fleet Requirement](image)

Figure 2.10: SPT Fleet Size Requirements for New Jersey [19]

Based on Brownell and Kornhauser’s findings this thesis only examines an SPT model for the Manhattan ATN, given that it was found to be better than the PRT alternative. This thesis also uses updated 2016 data for a more accurate look at the demand landscape in Manhattan on a typical weekday. It examines the affects of ride-sharing on trip distributions and looks at fleet requirements to find the most optimal system for implementation - something that has yet to be done specifically for Manhattan.
Chapter 3

The Case for Autonomous Vehicles

The case for autonomous vehicles derives from four main areas: safety, environment, traffic and congestion, and efficiency. The World Economic Forum estimates that the digital transformation of the automotive industry will generate $67 billion in value for the sector and $3.1 trillion in societal benefits upon full adoption. The digital transformation of the automotive industry not only includes the development of autonomous technology, but the resulting cars that become large mobile devices housing an incredible amount of data, processing power, and content. AVs will bring benefits in the spheres of environment, economy, congestion, and safety as well as utility, data processing, and the inter-connectedness of the world. Efficiency will increase, not only in the realm of lessened congestion but also in terms of time spent while in the car. Drivers become full-time passengers, leaving time for work, phone calls, games, and many other activities.

3.1 Safety

Perhaps the most obvious and compelling argument for AVs relates to safety. The main idea behind this argument is that AVs can reduce the rate of crashes due to human error. Someday, a car crash has the potential to have the same shock value as an airplane crash. If technology can be trusted to remove human driver error, society can benefit hugely from these self-driving machines, avoiding crashes and keeping not only passengers, but pedestrians and cyclists safe as well. Extremely accurate digital imaging technologies
in AVs allow for these improvements. In facial recognition, for example, humans have an error rate of 0.8 of one percent, whereas computers with image recognition software have an error of only 0.23 of one percent. And in terms of visibility, humans can see only fifty meters down the road, compared to 200 meters for AVs equipped with LiDAR beams and cameras. This increase in capability has the potential for a severely reduced number of accidents.

Traffic and transportation-related data from the U.S. Department of Transportation (USDOT) sheds light on the grim traffic-related fatality situation in the United States. Figure 3.1 below details the number of police-reported crashes from 2014 and 2015 broken down into “fatal” and “non-fatal” categories.

![Figure 3.1: Police-Reported Crashes by Severity](image)

Here one can see that there were 32,166 fatal traffic-related deaths in the United States in 2015 alone - an increase of +7.0% from 2014 and the largest increase in nearly fifty years. Fatalities increased in almost every category: passenger vehicle occupants, pedestrians, bicyclists, motorcyclists, alcohol-related, male, female, daytime, and nighttime. Crashes can result from environmental conditions, roadway imperfections, fault of a pedestrian or cyclist, or vehicle failure. According to the NHTSA, however, over 90 percent of crashes are attributable to human driver error. This is an incredibly significant statistic. Thinking linearly and assuming AVs would remove human driver error, that is an upper-bound potential for almost 29,000 lives saved in 2015 in the United States alone.

China’s fatal traffic accident problem is magnified to an even more extreme level given the larger population, number of cars on the road, and relatively unsafe driving environment with unmarked lanes as well as more cyclists and pedestrians. Using the most recent World
Health Organization road traffic deaths by country data, it is possible to see just how dire the situation in China is. China has the most traffic-related deaths in the world: around 260,000 fatalities a year. This figure is staggering when compared to the United States’ estimated 32,000. Another compelling statistic in China is that crashes have disproportionately affected adults over sixty-five - a demographic that would be one of the biggest beneficiaries of autonomous driving, lending mobility and accessibility to those with oftentimes no other means. Assuming the human driver as the cause of crashes in China is similar to the United States’ 90%, this marks an upper-bound potential of over 240,000 lives saved in the country upon the advent of AVs.

Besides the benefit of sheer number of lives saved, cutting costs is another reason better safety can improve the world. Simply put, crashes are expensive. The economic impact of crashes is crippling. The NHTSA released a report in February 2017 detailing the United States’ economic costs of crashes. It estimates the comprehensive cost of crashes to be $836 billion a year and the economic costs to be $242 billion, summarized in Figure 3.2 below. This is an overwhelming amount of money on top of the lives lost.

![Figure 3.2: U.S. Motor Vehicle Crash Costs](image)

Safety is obviously the paramount concern of the government, so it is not surprising that the context with which the autonomous driving argument is framed is often centered around...
this topic. This brings us to the question, though, of how much safer do autonomous cars have to be to earn acceptance from society? Is 90%, as we’ve seen in the United States and China, enough? Or would it have to be 99.9%? This question has yet to be answered, but given the number of other benefits AVs bring the government and public should carefully consider even a marginally safer alternative.

3.2 Environment

Vehicles are one of the largest polluters of the environment. According to data from the U.S. Environmental Protection Agency, shown in Figure 3.3 below, the transportation sector constituted 26% of greenhouse gas emissions in 2014, making it the second largest contributor behind electricity. Greenhouse gas emissions in the transportation sector come from burning fossil fuel for cars, trucks, ships, trains, and airplanes.

![Figure 3.3: 2014 U.S. Greenhouse Gas Emissions by Sector](image)

The inevitable break-up of individual car ownership culture and a turn toward SAVs and ride-sharing has large implications for improving the pollution from the transportation sector. According to two researchers at the University of Texas Austin, Daniel Fagnant and Kara Kockelman, preliminary results show that each SAV can replace around eleven
conventional vehicles, but also adds up to 10% more travel distance. Ratti, as cited in the previous chapter, estimates that each SAV is able to replace ten privately owned cars. Whether ten or eleven, this has the potential to create many fewer but more powerful vehicles. In 2009, the NHTSA estimated that the average vehicle occupancy (AVO) for a car in the United States was 1.55. A turn toward SAVs could increase the AVO dramatically, reducing the number of cars on the road and therefore the greenhouse gas emissions. The increase in AVO in the advent of ATNs will be shown in Chapter Five.

Another compelling environment-related argument is one that the KPMG report, “Self-Driving Cars: The Next Revolution,” cites as a fact published by the MIT Media Lab: “In congested urban areas, about 40 percent of total gasoline use is in cars looking for parking.” Commuters spend hours per year inching along in traffic, driving in circles looking for parking spaces, and idling. With an autonomous taxi system, the need to look for a parking space disappears, saving tons of gasoline.

Similar to road accidents, the pollution in China is magnified to a much more extreme level. In China, rising vehicle ownership coupled with pre-existing reliance on manufacturing and industrialization has created severe environmental consequences. As shown in Figure 3.4 below, Beijing’s monthly average PM2.5 concentrations are much higher than those of the most polluted city in the United States: Los Angeles.

![Figure 3.4: 2008-2014 Monthly Beijing Air Quality Averages](image-url)
The Chinese government has already taken many steps to reduce the number of cars on the road. Starting after the Beijing Olympics in 2008, a road space rationing program was implemented with regulations such as the even-odd license plate policy. If one’s license plate ends in an even number then that car cannot drive on an odd-number day. The impact that fewer cars on the road could have for pollution in China is a compelling reason to implement AVs and shared-ride services.

### 3.3 Traffic and Congestion

Traffic and congestion in the U.S. and China are dire problems, especially in cities. They add hours to commutes, create excess emissions, risk accidents, and waste time - a valuable asset in a person’s life. The levels of traffic and congestion in the U.S. have steadily increased over the last sixteen years. Rising vehicle sales and VMT indicate that there have been increasing trends in individual car ownership. Figure 3.5 below shows the rising vehicle sales over the past 20 years. Besides a dip after the 2008 financial crisis, vehicle ownership has been steadily increasing and was at 18 million during February 2017.

![Figure 3.5: U.S. Total Vehicle Sales](image)

Coupled with higher vehicle sales is an increase in VMT over the years on U.S. roads and highways. Table 3.1 below contains the VMT in the U.S. since 2000. There has been a 2.8% YTD increase from 2015 to 2016 alone, and a 17.1% increase since 2000. At the SAE World Congress in Detroit, Peter Phelps said the U.S. will remain the top “road-warrior nation,” with more annual miles driven than any other.[27] This undeniably leads to more
traffic and congestion. China’s vehicle sales, shown in Figure 3.6 below, have seen a similar trend - while more cyclical than U.S. vehicle sales, there is still a steady increase.

Table 3.1: Vehicle Miles Traveled in the U.S. [4], as of December 2016.

<table>
<thead>
<tr>
<th>Year</th>
<th>December</th>
<th>Year to Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>218,390</td>
<td>2,746,926</td>
</tr>
<tr>
<td>2001</td>
<td>229,584</td>
<td>2,795,611</td>
</tr>
<tr>
<td>2002</td>
<td>234,260</td>
<td>2,855,509</td>
</tr>
<tr>
<td>2003</td>
<td>238,538</td>
<td>2,890,222</td>
</tr>
<tr>
<td>2004</td>
<td>245,029</td>
<td>2,964,789</td>
</tr>
<tr>
<td>2005</td>
<td>245,787</td>
<td>2,989,430</td>
</tr>
<tr>
<td>2006</td>
<td>248,208</td>
<td>3,014,371</td>
</tr>
<tr>
<td>2007</td>
<td>240,363</td>
<td>3,030,615</td>
</tr>
<tr>
<td>2008</td>
<td>242,231</td>
<td>2,981,806</td>
</tr>
<tr>
<td>2009</td>
<td>239,703</td>
<td>2,961,896</td>
</tr>
<tr>
<td>2010</td>
<td>240,998</td>
<td>2,969,720</td>
</tr>
<tr>
<td>2011</td>
<td>244,930</td>
<td>2,951,104</td>
</tr>
<tr>
<td>2012</td>
<td>238,715</td>
<td>2,968,248</td>
</tr>
<tr>
<td>2013</td>
<td>241,302</td>
<td>2,987,275</td>
</tr>
<tr>
<td>2014</td>
<td>252,394</td>
<td>3,025,265</td>
</tr>
<tr>
<td>2015</td>
<td>262,332</td>
<td>3,130,460</td>
</tr>
<tr>
<td>2016</td>
<td>263,641</td>
<td>3,217,956</td>
</tr>
</tbody>
</table>

Figure 3.6: China Total Vehicle Sales [9]

According to a 2017 study done by INRIX, population, economic growth, and continued urbanization are the root causes of congestion. [25] American cities, they find, dominate the
top ten most congested cities, with Los Angeles (first), New York (third), San Francisco (fourth), Atlanta (eighth), and Miami (tenth). According to the report, commuters in Los Angeles spent 104 hours last year in traffic jams - more than any other city in the world. New York City commuters sat in traffic for eighty-nine hours on average, the second most of any North American city and third most globally. Across the 1,064 cities studied, drivers spent an average of 9 percent of their time in traffic, and the average speed in congestion was 8.9 mph.

Uber’s website has a graphic, illustrated below in Figure 3.7, that represents the congestion within San Francisco before and after the implementation of UberPOOL. The high congestion areas, shown in yellow, are nonexistent in the advent of this ride-sharing service.

![Figure 3.7: Traffic in San Francisco Before and After Implementation of UberPOOL](image)

Given these trends and known results from UberPOOL, it will be important in the future for AVs to lessen the number of cars on the road, and hence the traffic and congestion. As mentioned before, it is estimated that each SAV could replace about ten individual cars. Having connected AVs will also help with traffic flow and operations. As envisioned by the USDOT Connected Vehicles program, one purpose of the connected environment is to reduce congestion and enhance mobility. From a traffic operations perspective, a key focus of connected vehicle systems is enabling coordinated strategies that improve the quality of flow along highways and at intersections, including speed harmonization, coordinated cruise
control, and queue warning. Fewer cars on the road as well as the implementation of connected vehicles will help lessen congestion in major cities.
Chapter 4

Implementation in China

China, with 126 million private vehicles on the road, will have to make a significant shift once autonomous ride-sharing becomes a more prevalent phenomenon. Thirty-five cities have more than one million cars on the road. Ten cities have more than two million. And in the country’s busiest urban areas, almost 75% of all roads suffer rush-hour congestion. Beijing alone has 5.6 million vehicles in operation.

From its culture and technological resources to its corporate development and governmental attitude toward AVs, China has compelling reasons for being one of the earliest adopters of AV technology. The Society of Automotive Engineers of China (SAEC) and the Ministry of Industry and Information Technology (MIIT) have issued a 450-page roadmap titled “The Technology Road Map For Energy Saving and New Energy Vehicles” that lays out the blueprint for the development of virtually every aspect of the automotive industry until 2030. The roadmap “forges a consensus within China’s auto industry so that the country can rapidly move towards producing and selling self-driving cars.” Meanwhile, the lack of such a consensus may suppress AV development in other countries. The report states that some form of automated or assisted driving should be in every car by 2026 to 2030. This chapter looks at what makes China poised for driverless cars and also examines some of the obstacles the country will face in its pursuit.

1Much of this chapter’s research is based on my trip to China to survey the autonomous vehicle environment. I met and consulted with business leaders and developers of the technology while in Beijing.
4.1 Why China?

China, with over 1.3 billion people, has been one of the most talked-about countries in the world over the past thirty years. From its history and rich culture to its undeniable economic development, China has, as Benjamin Page and Tao Xie describe in their book *Living with the Dragon: How the American Public Views the Rise of China*, “burst forth onto the world scene in a big way - first with increased exports to and imports from more and more countries around the globe; then with broader political and diplomatic influence around the world; and eventually with extensive investment and aid abroad.”[17] China has entered the world stage via its trade and political influence, and has become an increasingly innovative country in the process.

In the realm of AVs, China is one of the most compelling countries to focus on for two primary reasons. First, China has a dire need for the benefits AVs will bring. With the largest population in the world and a very high urban percentage, the most traffic-related deaths, and one of the largest pollution problems on the planet, China needs a solution. AVs mitigate each of these issues. Second, China’s culture, style of innovation, and governmental system will ensure that it will be one of the first successful countries to make the leap towards fully autonomous vehicles and ride-sharing systems.

China’s extremely large population and fast development have led to difficulties the country has yet to solve, mostly relating to the question of how to progress at a high level while maintaining safety, environmental protection, and efficiency. While China’s private vehicle sales and car ownership have gone up dramatically, shown below in Figure 4.1, so has the multitude of problems that come with it. As previously mentioned, China has the most traffic-related deaths in the world, at 260,000 per year.[20] Beijing’s level of pollution is much greater than that of Los Angeles on any given day. And Beijing isn’t even China’s most polluted city. The figures are staggering. China knows it will have to remedy these issues if it wants to be a respected world power. The implementation of AVs in China is therefore a necessity.

Another factor contributing to its “need” for AVs is China’s population demographics. By 2050, it is estimated that senior citizens will comprise 33 percent of the overall
population, compared with the U.S.’s estimated 20 percent. A key motivator for the implementation of driverless cars is providing enhanced mobility to all: the sick, disabled, young, elderly, intoxicated, and so on. Due to China’s one-child policy, coupled with other factors, the Chinese population is set up to resemble that of an inverted triangle - a high proportion of elderly people and not enough young and working-aged people to prop up the economy. This means that China will have a very large elderly population in need of mobility, so putting these cars on the road will become ever more important.

Separate from need, China’s culture and approach toward innovation lend it many advantages in the race to a fully autonomous society. In George Yip and Bruce McKern’s book *China’s Next Strategic Advantage: From Imitation to Innovation*, the chapter “What is Different About Chinese Innovation?” helps detail China’s assets. Yip and McKern outline ten major ways in which Chinese companies’ innovation activities differ, specifically, from other multinational corporations. Some key advantages applicable to China’s self-driving car development are the greater focus on local needs and customers, acceptance of “good enough” standards, incremental rather than radical innovation, deployment of large numbers of employees and working them harder, faster and less formal processes, and, importantly, closer ties to government. China’s growing culture of innovation has helped development as well. The Chinese government reported that “4.8 million new companies
were registered from March 2014 to May 2015, a rate of 10,600 new business per day, or seven every minute. The CCP is encouraging this boom as a way to solve economic problems, such as unemployment and the transition of the economy from one centered on manufacturing to one based on services. China’s type of innovative culture lends the country undeniable advantages.

As mentioned, China’s innovation style differs from others in distinct ways. First, a greater focus on local needs and customers allows for a better understanding in terms of what kind of AV implementation society is looking for. Yip and McKern argue that the rapid growth of China’s economy causes customers’ needs to evolve more quickly than they do in developed countries, which, in turn, causes Chinese firms to focus more intently on those needs. Consideration and emphasis on the part of companies regarding consumers breeds some level of trust and understanding between society and the businesses developing these cars. Given that the driverless phenomenon is coming and there is an existing covenant of trust between people and companies, society may be less apprehensive and more accepting of AVs, making China a likely early adopter.

Acceptance on the part of companies of “good enough” standards also allows for early adoption of, and hence a quick trial and error period for, driverless cars. This is related to having faster, less formal processes. Yip and McKern state that in contrast to multinational companies, “most Chinese companies are starting from the bottom end of markets, so their initial challenge is building up, not down, to standards that are good enough for China.” They also argue that Chinese companies are motivated to innovate in a much faster way, whereas multinational companies are constrained by formal, bureaucratic processes imposed by higher ups. China’s method allows companies to develop AVs that serve the “least demanding” customers first. With this bottom-up approach, Chinese companies and the government will be able to improve the technologies and implementation details of self-driving cars and aTaxi systems in a more efficient, step-by-step way than other Western countries. In the United States, for example, the AVs that are rolled out will have to be near-perfect before society and the government will fully accept them, causing a delay in adoption.
Deploying large numbers of employees under rigorous work standards is an asset China’s large population and work-first culture lend. Its low cost of employment - well below those of other advanced countries - is a significant advantage in developing technologies and performing large-scale innovations. Work ethic is spurred by individual incentives, competition, and national pride. Yip and McKern talk about the so-called “wolf-spirit” of Huawei, one of the leading global information and communications technology firms. Ren Zhengfei, the founder and chairman of the company, has said, “Huawei people, especially the leaders, are destined to work hard for a lifetime and to devote more and suffer more than others.” This prioritization of work over leisure makes China an increasing global leader in innovation.

Most importantly, Chinese companies have much closer ties to government than in many other countries. Yip and McKern state that one-party rule coupled with high levels of state ownership and intervention require both private and state-owned Chinese companies to work much more closely with the government than most Western firms. Unlike Google, which has experienced challenges convincing regulators in California that self-driving cars are ready for the road, Baidu already has the regulatory and infrastructure support of a number of local Chinese governments. Another factor behind the Chinese government’s progressiveness in terms of ride-sharing and AV implementation is that its motivation stems from a feeling of needing to “catch up” because of China’s late arrival to the automotive industry. This desire to compete and reach other competitors in the industry will surely be a powerful drive and help push forward regulatory measures to keep up with the technology. Given that government regulation is one of the largest hurdles for AV implementation, close governmental ties give China a significant advantage in adoption.

China seems to have an ideal combination of need and drive for the development and implementation of AVs. Xavier Mosquet, a managing director at BCG, asserts that “It’s not that people are more willing to use the cars in Beijing or Shanghai, it’s that the economic value is much higher in China than in the U.S.” Perhaps it is, in fact, both elements - more of a willingness and a higher economic value. As one New York Times article states, China, unlike the United States, never fully developed a romance with the open road and car ownership. A Roland Berger survey supports this, noting “51 percent of Chinese car
owners said they would prefer to use robot taxis rather than buy a new vehicle themselves, compared with 26 percent of Americans.” Figure 4.2 below illustrates that Chinese consumers are indeed more willing to buy cars from technology companies than those in the U.S. and elsewhere. This survey, with over 7,500 respondents, shows that 74% of Chinese consumers would be willing to purchase technology company cars, compared to the U.S.’s 29%. Wang Jing, the head of Baidu’s autonomous vehicle program, cites three factors in China’s favor: a population prone to embracing new technology, a vast auto industry, and a national appetite for big, bold projects. Given this, China seems to have the advantage in both aspects - higher economic value as well as societal willingness. Add in governmental support and regulatory cooperation and China will become the largest and potentially most successful market for AVs and autonomous ride-sharing platforms.

4.2 Market Potential and Approach

According to a BCG report, China is expected to have the highest number of AVs in the world by 2035, with close to 8.6 million units, including 5.2 million that are partially
autonomous and 3.4 million fully autonomous. Industry officials also believe that “the Chinese market for car sales, buses, taxis and related transportation services is potentially worth more than $1.5 trillion a year in revenue.” According to Michael Dunne, president of Dunne Automotive Ltd. in Hong Kong, partially-autonomous cars are to account for 50 percent of sales by 2020. Highly-automated cars will make up 15 percent of sales in 2025. And by 2030, fully autonomous vehicles are expected to take 10 percent of sales, or four million fully autonomous cars annually. This makes China’s market potential for AVs, and thus ride sharing, the largest in the world.

Baidu is one of the preeminent companies in China working on AVs. While much of car production and auto technology has typically been developed outside of China, the country has certain technological advantages when it comes to driverless cars. Baidu’s Wang Jing stated:

Chinese carmakers started making cars 100 years after others and a lot of the core technology aren’t in Chinese hands, such as engines. With electric cars, with intelligent cars, the core technology shifts from the engine and gearbox to artificial intelligence and that’s an area where China is very close to the U.S., giving China the chance to catch up and seize leadership.

Baidu’s co-founder and CEO, Robin Li, has invested heavily in deep learning, which aims to improve search results and computing tasks by training computers to work more like the human brain. Attacking AV development from this angle will allow China to leverage its artificial intelligence (AI) and deep learning expertise, placing China on the global stage for earliest adoption and development of a Taxi fleets. Michael Dunne says something along the same lines:

Chinese Internet companies like Baidu, flush with cash and confidence, are jostling for leadership in the holy trinity of the auto industry’s future: electrics, car sharing and - autonomous cars. Google enjoys a huge lead in autonomy today. But don’t underestimate the Chinese will to compete.

Competing from the angle of software and deep learning is an advantageous approach to attacking the AV market.
On implementation in China versus the U.S., Uisee Technology’s co-founder Jiang Yan reiterated much of what research has shown. The two countries will take varying approaches and different technologies will be realized first in each. For example, a low speed autonomous shuttle will most likely be implemented in China first. Given that the shuttle can only cover about a five mile radius and people in the U.S. live too far from each other, this development will be more applicable in China. Autonomous trucks, however, he believes will be realized in the U.S. first due to the fact that the cost of labor is low in China and lowering the burden of truck drivers is more important in America.

China’s AI and deep learning approach will aid developers in coming at the AV challenge from a unique angle. Its approach differs in many other ways as well, which Jiang Yan helped explain. A co-founder of Uisee, he discussed his company and thoughts on the future of AVs. He described the team as experts from every aspect - the Google employee specializes in vision and perception, Wu in computation and software, and Jiang Yan himself in mechanics and control. Uisee is a complete system. Jiang Yan and Uisee have taken the approach of trying to aid drivers instead of replacing them. While many companies are trying to get driverless cars on the road as quickly as possible, Uisee has a different strategy. Jiang Yan believes in having high speed automated driving for passenger vehicles, but keeping the driver as a backup. Unmanned vehicles, he says, should only be in limited situations like restricted zones at slow speeds. This approach was confirmed again at an August 2016 Artificial Intelligence Symposium in Beijing where Yang Yi, a professor at the Beijing Institute of Technology and developer of Baidu’s first self-driving car, emphasized China’s focus on augmenting human intelligence instead of replacing it in the realm of AVs. This perspective illustrates China’s step-by-step approach and will lend the country an advantage in AV rollouts.

Studying China’s market approach also introduces the question of competition between China and other countries, specifically the U.S. China’s self-driving road-map has confronted global automakers with a choice: share their best electric and autonomous technology with

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2On my research trip to Beijing I sat down with Jiang Yan, who had many things to say about China vis-a-vis autonomous vehicles.

3While in Beijing, I attended the Artificial Intelligence Symposium at the China Hall of Science and Technology on August 18, 2016.
Chinese partners, or potentially get sidelined in the world’s largest market. According to Dunne, China accounts for more than a third of global sales for several foreign automakers - Audi, VW, and GM included - which does not lend companies much leverage when negotiating with Chinese firms. A recent article published in the *New York Times*, titled “China Tech Investment Flying Under the Radar, Pentagon Warns,” outlines a report released by the Pentagon cautioning that heavy Chinese investment in American technologies is causing the U.S. to lose its strategic advantages over China. The report states, “If we allow China access to these same technologies concurrently, then not only may we lose our technological superiority, but we may even be facilitating China’s technological superiority.”

Velodyne, a U.S. company that develops LiDAR technology, recently received a $150 million joint investment from Ford and Baidu for the stated purpose of making advanced LiDAR sensors more accessible to the broader industry, resulting in the development of safer, less expensive AVs. Hong-Kong traded Tencent recently took a 5 percent stake in Tesla for $1.78 billion. According to a Tesla report, China imported 11,839 Tesla vehicles in 2016, nearly five times the prior year. The firm’s analysis also showed that China’s market share in global shipments jumped from 5 percent to 16 percent from the previous year. Tesla has seen substantial success in China and, coupled with Tencent’s new stake in the company, Elon Musk and his team will need to balance their desire to succeed in China with the Pentagon’s forewarnings. While the technological race between the two countries has often been portrayed in an economic light, the Pentagon emphasizes the potential national security threat. The United States and China already have a vulnerable relationship on many fronts - sovereignty over territories, human rights, and North Korea, to name a few - so adding more potential conflict over AV development, data-sharing, and espionage complicates the two countries’ relations even further.

### 4.3 Challenges

All countries working on AVs will encounter a variety of obstacles, from development and implementation to regulatory pushback. China’s main challenges seem to stem from technology, infrastructure, regulation, and societal acceptance.
In terms of technology, Yang Yi mentioned that a big problem in China are sensors, which are typically developed in foreign countries. He reiterated that there is lots of programming but not enough hardware - perhaps a reflection of China’s late arrival to the auto industry. Systems like LiDAR, actuators, processors, and other types of sensors are harder to come by in China. As such, Chinese companies will need to continue partnering with foreign firms to gain the technologies they are missing or catch up in the development of them.

In the realm of infrastructure, China will have to make serious investments for an AV-friendly environment. The driving conditions are incredibly variable in China - roads are frequently unmarked, lanes are inconspicuous, and there is usually a significant number of bikes and motorcycles crowding the roads in cities. If car cameras cannot read road and lane markings then HD maps aren’t useful. Self-driving cars work best in an environment of limited variables where everyone follows set rules and so far, most of the automakers and technology firms around the world racing to develop the technology have tested them on highways or quiet suburbs. China’s driving environment and urban traffic landscape as it stands is complex and chaotic - not the ideal domain for AVs.

Regulation, as previously discussed, also poses challenges for companies developing AVs. While China does not necessarily have the same fragmentation problem as the United States, the various ministries have to figure out how to work together. One serious obstacle is China’s ban on AV testing imposed in 2016. Current rules require drivers to be in the vehicle and keep both hands on the steering wheel at all times. Fully autonomous vehicles can’t be tested under actual conditions unless there is government flexibility in granting road test exemptions, as it’s difficult to simulate actual highway driving through off-road sites. Another realm where regulation staunches progress is in HD map development. Due to security reasons, the Chinese government regulations mandate that public maps cannot be more accurate than fifty meters. Four articles in China’s Surveying and Mapping Law of the People’s Republic of China legislation have specifically prohibited the generation

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I met with Yang Yi separately from the Artificial Intelligence Symposium. We met in his office at the Beijing Institute of Technology and talked through his progress and China’s future in the realm of AVs. We then went to his lab to look at some of the autonomous vehicles he and his team are testing. Beijing Institute of Technology hosts the China arm of the Princeton Autonomous Vehicle Engineering (PAVE) lab; Yang Yi is the current head.
of “significant geographic information and data” in Chinese territory since 2002. While certain companies like Alibaba and Baidu have private maps with a much higher precision, this restriction prevents many companies from developing the accuracy required for HD maps. Companies need special licenses from the National Administration of Surveying, Mapping, and Geo-Information to collect certain road information. This limitation has caused many companies to seek partnerships with government-backed entities that already have coveted data. Because most western countries don’t have these types of restrictions, Chinese companies are at a competitive disadvantage until these bans are lifted or relaxed.

In terms of societal acceptance, China may come across some intangible challenges. While studies cited earlier have shown that the Chinese are more likely to use AVs over an individual car than Americans, this may not paint the full picture. China arriving late to the auto industry and individual car ownership phenomenon may not actually mean that they won’t fully “develop the romance” with car culture. Perhaps it is just beginning. Some argue that the individual car ownership sentiment is felt even stronger in China because of the recent uptake of personal possession and skyrocketing vehicle sales. Figure 4.3 below illustrates the different vehicle sale trajectories between the U.S., China, and Europe. Starting from near zero in 2000, China’s sales have risen sharply for the past fifteen

![Figure 4.3: Number of Family Vehicles Sold in the U.S., China, and Europe](image)

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51
years, overtaking both the U.S. and Europe. While rising vehicle sales do not conflict with society’s willingness to purchase and ride in AVs, the recent phenomenon poses a potential resistance to shifting permanently away from individual car ownership. If the adoption of AVs means a substantial shift away from personally-owned vehicles, China may not be ready quite yet. Many Americans remember growing up with cars, yet most Chinese have never owned one until recently. The feeling of individual ownership is one they might not want to give up. This challenge will remain to be seen, but there is certainly the possibility of societal attitude going either direction.
Chapter 5

Manhattan aTaxi Service
Implementation and Optimization

5.1 Problem Description

Finally, this thesis presents a solution to the autonomous ride-sharing service implementation problem in Manhattan. Manhattan, a complicated and incredibly dense city, has compelling reasons for being the choice metropolis for solving the autonomous taxi service implementation problem. Neighborhoods are relatively distinguishable, streets are on a gridded system, and given the level of congestion in Manhattan, an efficient aTaxi system would be a welcome solution to the heavy traffic. The problem has dual parts: first, through individual trip data analysis one can examine the vehicle transportation landscape of Manhattan by trip type, density, distance, and departure times. Then, using this individualized trip data, the problem becomes an optimization exercise to place individuals in aTaxis in the advent of a self-driving ride-sharing system. The level of service (LoS) is determined by constraints on number of stops an aTaxi can made (Common Destination = CD), waiting time (Departure Delay = DD), extra distance traveled (Max Circuity = MC), and passenger capacity. Knowing multiple peoples’ origins and destinations in a certain pixel, what is the best combination of people to ride-share and how would the service optimally decide where
and what order to pick up and drop off? This chapter programatically solves that problem for Manhattan. It then places aTaxi stands at the centroids of each pickup pixel.

5.2 Map and Population

It is helpful to look at a map of the working area to get a sense of the landscape and place the latitude and longitude of individual trips on the map for context. The map for this problem includes all of FIPS code 36061, or Manhattan. Figure 5.1 shows a snapshot of the working area in red for the problem:

![Figure 5.1: FIPS Code 36061 Coverage Map](image)

All trips analyzed in the problem both originate and arrive in the contiguous area of FIPS 36061. Figure 5.2 below shows a more detailed look at Manhattan, with its gridded street system and neighborhood breakdowns. The major neighborhoods are Washington Heights, Harlem, Upper East and West Sides, Midtown, East and West Villages, Tribeca, Chelsea, Soho, Lower East Side, and the Financial District (FiDi).
The city has a population of around 1.6 million, with a much larger commuting population on the weekdays due to workers and students coming into the city from other counties. There are close to four million trips on average each workday. The area is just under twenty-three square miles, making it the most densely populated county in the United States. Manhattan’s many neighborhoods have various concentrations of trip origination and destination types. The Upper East and West Sides, for example, are largely residential so trips originating and arriving in these neighborhoods will most likely be “Home”-type trips. Midtown and FiDi, on the other hand, will likely have more “Work”-type trips, given that many offices are located in those areas. Soho should have many “Other”-type trips,
given that it is a heavy shopping district. The concentrations of trip densities by type will be shown in Section 5.3.4.

5.3 Trip Data

Used in this problem is Kyle Marocchini’s Manhattan (FIPS code 36061) transit data to analyze a potential autonomous ride-sharing system in the city. As previously mentioned in the introduction, the data was generated from a hybrid Agent- and Activity-based model. The assignments of workplace, school, and trip destination were done using a Gravity Model, shown below in Equation 5.1. He used the Gravity Model to estimate the interaction between two counties, ascribing a “gravitational” pull to a location.

\[
T_{i,j} = P_i \frac{A_j F_{i,j} K_{i,j}}{\sum_{j=1}^{n} A_j F_{i,j} K_{i,j}}
\]  

(5.1)

where:
\( T_{ij} \) = number of trips from zone i to zone j
\( P_i \) = number of trip productions in zone i
\( A_j \) = number of trip attractions in zone j
\( F_{ij} \) = friction factor representing the spatial separation between zone i and zone j
\( K_{ij} \) = optional adjustment factor

The Gravity Model Marocchini used increases with popularity of the destination and decreases with distance squared. An example of that used to assign workplace in his data set is shown below in Equation 5.2:

\[
w_{h,c} = \frac{x_{h,c}}{\sum_j x_{h,c}^2}
\]  

(5.2)

where:
\( h \) = the index of the worker’s home county
\( C \) = the set of commutable counties for workers in county \( h \)
\( x_{h,c} \) = the number of workers commuting from county \( h \) to \( c \)
\( D_{h,c} \) = the distance between the centroids of counties \( h \) and \( c \)

\( w_{h,c} \) = the weight of attraction for a worker commuting from county \( h \) to \( c \)

Marocchini then pixelized the data by breaking up Manhattan into a grid in which each pixel had a side length \( d_s = 0.5 \). The data will be repixelized in Section 5.4.1 with \( d_s = 0.3 \) to better suit Manhattan’s compactness as a problem setting.

The resulting trips span the full day of December 8, 2016, from 12:00A.M. through 11:59P.M. The data includes trips originating from and arriving within FIPS code 36061 and is split into six different files. First, all trips with a destination outside of 36061 (DFIPS \( \neq 36061 \)) were removed to get a contiguous area within Manhattan. The six files were then combined to get one large Manhattan trip file for complete analysis. There are a total number of 3,892,232 individual trips on December 8, 2016 within the county.

Figures 5.3 and 5.4 show snapshots of the excel data. The columns are explained in Table 5.1 below.

Figure 5.3: Manhattan Trip Data, Columns Country Code through OYCoord

<table>
<thead>
<tr>
<th>County Code</th>
<th>Person ID</th>
<th>Trip Type</th>
<th>OType</th>
<th>OName</th>
<th>DFIPS</th>
<th>Dlon</th>
<th>Dlat</th>
<th>OXCoord</th>
<th>OYCoord</th>
</tr>
</thead>
<tbody>
<tr>
<td>36061</td>
<td>3454170</td>
<td>15 H</td>
<td>Home</td>
<td>15 H</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>36061</td>
<td>30721865</td>
<td>17 O</td>
<td>CEG META MEDIA INC</td>
<td></td>
<td>36061</td>
<td>-73.987484</td>
<td>40.786264</td>
<td>174</td>
<td>254</td>
</tr>
<tr>
<td>36061</td>
<td>3950001</td>
<td>19 H</td>
<td>Home</td>
<td>36061</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>36061</td>
<td>10021502</td>
<td>15 O</td>
<td>BETH ISRAEL MEDICAL CTR</td>
<td>36061</td>
<td></td>
<td>-73.982241</td>
<td>40.753333</td>
<td>176</td>
<td>253</td>
</tr>
<tr>
<td>36061</td>
<td>10027692</td>
<td>15 O</td>
<td>NVC DESIGN</td>
<td>36061</td>
<td></td>
<td>-73.961915</td>
<td>40.79606</td>
<td>178</td>
<td>262</td>
</tr>
<tr>
<td>36061</td>
<td>9873213</td>
<td>15 O</td>
<td>SALEM DAY CARE CTR</td>
<td>36061</td>
<td></td>
<td>-73.947041</td>
<td>40.811981</td>
<td>180</td>
<td>264</td>
</tr>
<tr>
<td>36061</td>
<td>10352277</td>
<td>19 H</td>
<td>Home</td>
<td></td>
<td>36061</td>
<td>-73.998556</td>
<td>40.822454</td>
<td>180</td>
<td>265</td>
</tr>
<tr>
<td>36061</td>
<td>13490054</td>
<td>17 O</td>
<td>ELIZABETH SETON PEDIATRIC CTR</td>
<td>36061</td>
<td></td>
<td>-73.995413</td>
<td>40.79521</td>
<td>174</td>
<td>254</td>
</tr>
<tr>
<td>36061</td>
<td>9922112</td>
<td>15 O</td>
<td>123 LOCKSMITH</td>
<td>36061</td>
<td></td>
<td>-73.976707</td>
<td>40.785799</td>
<td>176</td>
<td>260</td>
</tr>
<tr>
<td>36061</td>
<td>9850904</td>
<td>19 H</td>
<td>Home</td>
<td></td>
<td>36061</td>
<td>-73.958737</td>
<td>40.79518</td>
<td>178</td>
<td>259</td>
</tr>
<tr>
<td>36061</td>
<td>10185684</td>
<td>19 H</td>
<td>Home</td>
<td></td>
<td>36061</td>
<td>-73.962674</td>
<td>40.820078</td>
<td>178</td>
<td>262</td>
</tr>
<tr>
<td>36061</td>
<td>3595146</td>
<td>15 O</td>
<td>NORTH SQUARE RESTAURANT-LOUNGE</td>
<td>36061</td>
<td></td>
<td>-73.998867</td>
<td>40.702317</td>
<td>174</td>
<td>253</td>
</tr>
</tbody>
</table>

Figure 5.4: Manhattan Trip Data, Columns ODepartureTime through GCDistance

<table>
<thead>
<tr>
<th>ODepartureTime</th>
<th>OType</th>
<th>OName</th>
<th>DFIPS</th>
<th>Dlon</th>
<th>Dlat</th>
<th>OXCoord</th>
<th>OYCoord</th>
<th>GCDistance</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 H</td>
<td>Home</td>
<td></td>
<td>-73.9781</td>
<td>40.775819</td>
<td>176</td>
<td>259</td>
<td>0.69552.7625</td>
<td></td>
</tr>
<tr>
<td>0 O</td>
<td>SPRINGBOARD PARTNERS IN CROSS</td>
<td>-73.991535</td>
<td>40.732301</td>
<td>175</td>
<td>253</td>
<td>0.87320291</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 H</td>
<td>Home</td>
<td></td>
<td>-73.991535</td>
<td>40.732301</td>
<td>175</td>
<td>253</td>
<td>0.87320291</td>
<td></td>
</tr>
<tr>
<td>0 H</td>
<td>Home</td>
<td></td>
<td>-73.95419</td>
<td>40.803478</td>
<td>179</td>
<td>265</td>
<td>0.653370537</td>
<td></td>
</tr>
<tr>
<td>0 O</td>
<td>Home</td>
<td></td>
<td>-73.95419</td>
<td>40.803478</td>
<td>179</td>
<td>265</td>
<td>0.653370537</td>
<td></td>
</tr>
<tr>
<td>0 O</td>
<td>WESTIN NEW YORK TIMES SQUARE</td>
<td>-73.988484</td>
<td>40.757503</td>
<td>175</td>
<td>256</td>
<td>5.03789478</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 H</td>
<td>Home</td>
<td></td>
<td>-73.9781</td>
<td>40.775819</td>
<td>176</td>
<td>259</td>
<td>0.69552.7625</td>
<td></td>
</tr>
<tr>
<td>1 O</td>
<td>RAYMOND JAMES</td>
<td>-73.974164</td>
<td>40.753519</td>
<td>177</td>
<td>256</td>
<td>1.866019395</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 O</td>
<td>FORD MODELS INC</td>
<td>-73.991703</td>
<td>40.738531</td>
<td>175</td>
<td>254</td>
<td>4.651180408</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 H</td>
<td>Home</td>
<td></td>
<td>-73.962981</td>
<td>40.756228</td>
<td>178</td>
<td>256</td>
<td>2.48739798</td>
<td></td>
</tr>
</tbody>
</table>
Table 5.1: Individual Trip File Columns

<table>
<thead>
<tr>
<th>Column Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>County Code</td>
<td>FIPS code of the area. All 36061 for this problem.</td>
</tr>
<tr>
<td>Person ID</td>
<td>Unique ID associated with each individual. Person IDs allow tracking of people who take multiple trips.</td>
</tr>
<tr>
<td>Trip Type</td>
<td>Trip type number indicates whether a trip is “Home” to “Work,” “Other” to “Other,” etc.</td>
</tr>
<tr>
<td>OType</td>
<td>Origin type. Possible values are Home (H), Work (W), School (S), and Other (O).</td>
</tr>
<tr>
<td>OName</td>
<td>Name of origin. Possible values are “Home,” “Westin New York Times Square,” “JP Morgan Chase Co.,” etc.</td>
</tr>
<tr>
<td>OFIPS</td>
<td>Origin FIPS code. All 36061 for this problem.</td>
</tr>
<tr>
<td>OLon</td>
<td>Origin longitude coordinate.</td>
</tr>
<tr>
<td>OLat</td>
<td>Origin latitude coordinate.</td>
</tr>
<tr>
<td>OXCoord</td>
<td>X-pixel associated with origin longitude coordinate.</td>
</tr>
<tr>
<td>OYCoord</td>
<td>Y-pixel associated with origin latitude coordinate.</td>
</tr>
<tr>
<td>ODepartureTime</td>
<td>Departure time of vehicle from origin.</td>
</tr>
<tr>
<td>DType</td>
<td>Type of destination. Same possible values as origin type.</td>
</tr>
<tr>
<td>DName</td>
<td>Name of destination.</td>
</tr>
<tr>
<td>DFIPS</td>
<td>Destination FIPS code. All 36061 for this problem.</td>
</tr>
<tr>
<td>DLon</td>
<td>Destination longitude coordinate.</td>
</tr>
<tr>
<td>DLat</td>
<td>Destination latitude coordinate.</td>
</tr>
<tr>
<td>DXCoord</td>
<td>X-pixel associated with destination longitude coordinate.</td>
</tr>
<tr>
<td>DYCoord</td>
<td>Y-pixel associated with destination latitude coordinate.</td>
</tr>
<tr>
<td>GCDistance</td>
<td>Great circle distance of trip, in miles.</td>
</tr>
</tbody>
</table>
The blue highlighted trip helps illustrate the data. The individual “10352677” originates from Home (-73.94496, 40.822454) in pixel (180,265) and his or her destination is at Westin New York Times Square (-73.988484, 40.757503) in pixel (175, 256). The vehicle departs at 0 seconds, or right at 12:00A.M. The trip’s distance is 5.04 miles and it is a “Home to Other” type trip.

5.3.1 Trips by Type

It is helpful to analyze the types, times, and distances of these Manhattan trips. First, looking at the data, one can see the breakdown of origin types in Figure 5.5. For origins throughout the day, most trips (49%) come from home. 38% come from “Other,” 8% from “Work,” and 6% originate from “School.” The destination trip type breakdown shows a different distribution, as illustrated in Figure 5.6. Most trips end at “Home” (42%), followed by “Other” (38%), then “Work” (16%), and “School” (4%).

It is also illustrative to analyze the type of trip distributions on a given day in Manhattan. Figure 5.7 displays the breakdown for each type of trip: Home to Other, Home to Work, Other to Other, School to Home, etc. Those not shown in the chart either have zero trips associated (Home to Home, Work to Work, etc.) or make up too small of a percentage (Other to Work, School to Work, etc.) to be relevant.

The most popular types of trips are Other to Home (31%), Home to Other (29%), and Home to Work (16%). New Yorkers spend a lot of their time traveling to and from
“Other” activities. The low number of school trips probably indicates that many children live in walking proximity or take the subway rather than driving, which makes sense for Manhattan. The imbalance of Home to Work and Work to Home is probably best explained by the fact that many employed adults in Manhattan don’t return straight home after work - they either pick up their children from school, go to a restaurant or bar, or attend some type of “Other” activity such as a doctors appointment or shopping.

Given the breakdowns of trips by type, it is useful to visualize the origin concentrations on a map. Figure 5.8 below shows density heat maps by trip type. All the longitude-latitude coordinates for each trip type were imported into QGIS software to generate the heat maps. As one can see, home-type trips are relatively spread throughout the city, with heavy concentrations in the Upper East and West Sides as well as the East Village. There are comparatively light concentrations around Tribeca and FiDi. Other-type trips are heavily concentrated within Times Square, Midtown and Fifth Avenue, as well as The Metropolitan Museum. Work-type trips are unsurprisingly concentrated exclusively within Midtown and FiDi. Finally, the school densities are dotted throughout the city with a high concentration in the Upper East and West Sides, the primary family and residential areas.
Figure 5.8: Density Heat Maps by Trip Type
5.3.2 Trip by Distance

Also important is the distance distribution of Manhattan trips, which is skewed left given the small size and compactness of the city. While the maximum trip is 13.15 miles, most trips are less than one mile. The trips for the distribution below in Figure 5.9 are bucketed into 0.1 mile intervals: 0-0.1 miles, 0.1-0.2 miles, etc. It is clear that the distribution is shifted much more towards shorter trips. There is a sizable amount of trips in between 0 and 0.25 miles (walking-length trips), but the number of trips spikes at around 0.5 miles, with a peak at 0.55 miles consisting of 285,782 trips. Trips between a half and one and a half miles are the most common. The number of trips trails off at around three miles and drops close to zero at nine miles. The jump from less than 0.5 miles to greater than 0.5 miles makes sense given that most people in Manhattan will walk if their destination is less than 0.5 miles away since the city is walking-friendly and people are relatively active. The drop-off around three to seven miles also makes sense given the small geographic area used for this problem.

Figure 5.9: Manhattan Individual Trip Distance Distribution
Figure 5.10 below shows the cumulative distribution of trip distances as the day progresses. The CDF is heavily skewed toward shorter length trips and the total distance covered throughout the day sums to 9,007,179 miles, otherwise known as the person trip miles served.

![Manhattan Individual Trip Distance Cumulative Distribution Function](image)

Figure 5.10: Manhattan Individual Trip Distance Cumulative Distribution Function

### 5.3.3 Trips by Departure Time

Finally, the data gives information about departures per minute. This is useful for judging individual demand throughout the day. The peak, as seen in Figure 5.11, is at 8:20 A.M. with 33,624 trips departing that minute. There are other peaks throughout the day shown in Table 5.2 below. The trip volume between the hours of 12:00-7:00 A.M. and 1:00-3:00 P.M drops close to zero because very few people are traveling in the early morning and in the early afternoon, given that school is still in session, lunch hour has passed, and adults are probably still at work. The busiest times are the commute to work after 8:00 A.M.,
late morning right before 11:00A.M, mid-afternoon at about 3:00P.M., the commute home from work at 5:00P.M., and the return of later workers at 8:00P.M.

Figure 5.11: Manhattan Individual Trip Departures per Minute

Table 5.2: Individual Trip Departure Peaks

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Number of Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:20 A.M.</td>
<td>33,624</td>
</tr>
<tr>
<td>8:48 A.M.</td>
<td>25,529</td>
</tr>
<tr>
<td>10:48 A.M.</td>
<td>14,451</td>
</tr>
<tr>
<td>3:31 P.M.</td>
<td>28,708</td>
</tr>
<tr>
<td>5:01 P.M.</td>
<td>22,233</td>
</tr>
<tr>
<td>8:01 P.M.</td>
<td>13,295</td>
</tr>
</tbody>
</table>

5.3.4 Demand Hotspots

It is helpful to also look at a heat map of the Manhattan trips to get a sense of where the demand hotspots are. Figure 5.12 maps out the hotspots from the full trip data, with
the darker blue spots signifying areas of greater density and the lighter blue signifying low density.

Figure 5.12: Density Heat Map of Manhattan Trips

The map, broken down into uptown and downtown in Figures 5.13 and 5.14, shows the more specific attractions. Some hotspots are easily distinguishable on the maps: Midtown,
for example, has some of the heaviest traffic. The Metropolitan Museum, Mount Sinai hospital, and Soho’s main shopping street, Broadway, also show higher density and hence are darker blue areas. These visual results substantiate Marocchini’s synthesized data, given that the geographic density of trips within the city are all in places one would expect the most traffic to come out of - FiDi, Soho, Midtown, Upper East Side, and so on.

![Figure 5.13: Density Heat Map of Downtown Trips](image1)

![Figure 5.14: Density Heat Map of Uptown Trips](image2)

### 5.4 Autonomous Taxi Ride-Sharing Analysis in Manhattan

With an idea of Manhattan’s transportation demand landscape, it is possible to use the person-trip data in order to place individuals into an ATN. The goal is to take Marocchini’s trip files and generate a set of aTaxi vehicle trips, assuming different passenger capacity aTaxis, departure delays, and max-circuits. Once an aTaxi trip file is generated for the whole county it is then possible to determine what the demand for an aTaxi service is at each pixel. The difference in number of trips taken, vehicle miles traveled (VMT), average vehicle
occupancy (AVO), and trip length and duration distributions are used as key performance indicators (KPIs) for analysis of an aTaxi network within the city.

5.4.1 Re-Pixelization of Manhattan Trip Data

Marocchini’s data has already been pixelized into dimensions 0.5 x 0.5 miles in side length. Given how dense Manhattan is, however, it is necessary to re-pixelize this data into smaller side length pixels. Following Kornhauser, et al.’s analysis of the New Jersey autonomous ride-sharing system, it is possible to pixelize the data by rearranging Equation 5.3. From there, using Equations 5.4 and 5.5, every \((Lon_o, Lat_o)\) pair is mapped to a smaller dimension pixel.

\[
D = \sqrt{(69.1(Lat_b - Lat_a))^2 + (69.1(Lon_b - Lon_a) \cos \left(\frac{Lat_a}{57.3}\right))^2}
\]  
(5.3)

\[
X_P = \frac{69.1}{d_s} \cos \left(\frac{Lat_p}{57.3}\right)(Lon_o - Lon_p)
\]  
(5.4)

\[
Y_P = \frac{69.1}{d_s}(Lat_o - Lat_p)
\]  
(5.5)

where:

- \(d_s\) = the length of each pixel side
- \((Lon_o, Lat_o)\) = the longitude-latitude pair of the trip
- \((Lon_p, Lat_p)\) = the longitude-latitude pair of the bottom left corner of the grid
- \((X_P, Y_P)\) = the x-y coordinates of the pixel for that trip’s longitude-latitude pair

The bottom left corner of the grid, \((0,0)\), corresponds to \((-74.1,40.6)\) in the pixelization of Manhattan. \(d_s = 0.3\) is chosen given that it allows for a tighter, more compact aTaxi network. With these variables, the equations simplify to

\[
X_P = \text{floor}(174.89(Lon_o + 74.1))
\]  
(5.6)

\[
Y_P = \text{floor}(230.3(Lat_o - 40.6))
\]  
(5.7)

67
All longitude-latitude pairs are assigned to the bottom left corner of each pixel. The resulting input data structure looks the same as in Figures 5.3 and 5.4, but there are more pixels associated with the latitude-longitude pairs given the decrease in pixel side length. This will allow for more aTaxi stands and thus shorter walks to the stands for those traveling.

5.4.2 Level of Service

This aTaxi service is set up under the model of the previously discussed SPT system, where the aTaxi will make various stops to pixels along the way to its final destination. This is in contrast to a PRT system that only makes one stop: its destination. The first important constraint in designing an SPT-type of service is that Common Destinations (CD) = 3, which means any given aTaxi will stop no more than three times in total after picking up passengers. Secondly, Departure Delay (DD) constraints are varied between 120 and 300 seconds (two and five minutes, respectively). As soon as a passenger gets into the aTaxi, it will wait no more than the departure delay constraint for other passengers to board before it departs. Maximum-circuit constraint of both 115% and 125% are experimented with. This constraint means that no passenger will travel more than 115% or 125% of the distance he or she would if going in a straight line from origin to destination. It is then possible to compare the trip length distributions by both distance and time. Finally, a vehicle capacity constraint is assumed. The aTaxi network is analyzed below for four, five, six, seven, and eight-passenger vehicles. Different passenger capacity constraints are experimented with to get a sense of the number of trips, miles traveled, and AVO for each size fleet for the purpose of comparison. What constraints are the most efficient and convenient for a Manhattan ATN?

5.4.3 Algorithm

The algorithm for this problem is modeled off the work of Bill Van Cleve, August Kiles, and Tianay Zeigler’s analysis of nationwide AVO in their report “Nationwide AVO,” with some significant alterations. The program iterates through each of the six Manhattan trip files in FIPS code 36061. An array “aTaxiBoarding” is introduced to keep track of all the aTaxis departing at each pixel. Once the algorithm reads in a departure from a given
pixel, the departure is entered into the aTaxiBoarding array and the first aTaxi is created to serve this trip. Each sequential trip is compared to the trips in each aTaxi that has not yet departed. If the origin, destination, and time of departure meet the constraints, then the person is added to a preexisting aTaxi barring capacity constraints. If the aTaxi that the person is added to already has multiple destinations then the route is reconfigured to be optimal. If, however, the individual’s trip does not meet the constraints of all available aTaxis then the program creates a new aTaxi for the rider. All aTaxis depart after the departure delay constraint has expired. The program loops through every person trip in each input file. See Appendix A for the algorithm’s detailed pseudocode.

5.4.4 Output

The algorithm then outputs an aTaxi trip file sorted by the numbered aTaxis picking up at each pixel. Snapshots of the output file are shown below in Figures 5.15 and 5.16.

<table>
<thead>
<tr>
<th>TaxiNo.</th>
<th>oXpixel</th>
<th>oYpixel</th>
<th>DepartureTime</th>
<th>RidersAtDeparture</th>
<th>CD1Xpixel</th>
<th>CD1Ypixel</th>
<th>CD2Xpixel</th>
<th>CD2Ypixel</th>
<th>RidersDeboardCD1</th>
<th>CD2Xpixel</th>
<th>CD2Ypixel</th>
<th>CD2Xpixel</th>
<th>CD2Ypixel</th>
<th>RidersDeboardCD2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13</td>
<td>20</td>
<td>57638</td>
<td>3</td>
<td>37</td>
<td>30</td>
<td>1</td>
<td>20</td>
<td>33</td>
<td>1</td>
<td>25</td>
<td>40</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>13</td>
<td>20</td>
<td>57969</td>
<td>2</td>
<td>25</td>
<td>39</td>
<td>1</td>
<td>25</td>
<td>40</td>
<td>1</td>
<td>25</td>
<td>40</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
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<td>13</td>
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<td>58134</td>
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<td>31</td>
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<td>40</td>
<td>1</td>
<td>25</td>
<td>40</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 5.15: aTaxi Trip Data, Columns TaxiNo. through Riders Deboarding at CD2

<table>
<thead>
<tr>
<th>CD3Xpixel</th>
<th>CD3Ypixel</th>
<th>RidersDeboardCD3</th>
<th>PersonTripMilesServed</th>
<th>DXpixel</th>
<th>DYpixel</th>
<th>ArrivalTime</th>
<th>aTaxiVehMiles</th>
<th>AVO</th>
<th>FIPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>37</td>
<td>1</td>
<td>23.779</td>
<td>19</td>
<td>37</td>
<td>60134</td>
<td>9.568</td>
<td>2.4852</td>
<td>36061</td>
</tr>
<tr>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>10.047</td>
<td>25</td>
<td>40</td>
<td>60786</td>
<td>11.736</td>
<td>1.4525</td>
<td>36061</td>
</tr>
<tr>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>20.676</td>
<td>25</td>
<td>40</td>
<td>61150</td>
<td>11.673</td>
<td>1.7712</td>
<td>36061</td>
</tr>
<tr>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>1.7977e+308</td>
<td>17.734</td>
<td>26</td>
<td>53</td>
<td>63125</td>
<td>17.734</td>
<td>1</td>
<td>36061</td>
</tr>
</tbody>
</table>

Figure 5.16: aTaxi Trip Data, Columns CD3Pixel through FIPS

The columns and descriptions are detailed in Table 5.3 below. The “1.7977e+308” values in CD2X, CD2Y, CD3X, and CD3Y columns mean that those values are undefined and are currently set to MATLAB’s “realmax” value. The columns containing that value simply indicate that no passengers are getting off at that destination.

An assumption used in the algorithm is that aTaxis in Manhattan will travel, on average, at fifteen miles per hour. Cars in Manhattan currently move at an average rate of close to ten miles per hour due to traffic and stops. In the future, with significantly fewer cars on
Table 5.3: aTaxi Output File Columns

<table>
<thead>
<tr>
<th>Column Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TaxiNo.</td>
<td>The numbered aTaxi picking up passengers for each pixel.</td>
</tr>
<tr>
<td>oXpixel</td>
<td>Origin pixel X-coordinate.</td>
</tr>
<tr>
<td>oYpixel</td>
<td>Origin pixel Y-coordinate.</td>
</tr>
<tr>
<td>Departure Time</td>
<td>The time of departure (in seconds) from the origin pixel.</td>
</tr>
<tr>
<td>Riders at Departure</td>
<td>Number of riders departing from origination pixel.</td>
</tr>
<tr>
<td>CD1XPixel</td>
<td>First common destination pixel X-coordinate.</td>
</tr>
<tr>
<td>CD1YPixel</td>
<td>First common destination pixel Y-coordinate.</td>
</tr>
<tr>
<td>Riders Deboarding at CD1</td>
<td>How many passengers will get off at the first destination.</td>
</tr>
<tr>
<td>CD2XPixel</td>
<td>Second common destination pixel X-coordinate.</td>
</tr>
<tr>
<td>CD2YPixel</td>
<td>Second common destination pixel Y-coordinate.</td>
</tr>
<tr>
<td>Riders Deboarding at CD2</td>
<td>How many passengers will get off at the second destination.</td>
</tr>
<tr>
<td>CD3XPixel</td>
<td>Third common destination pixel X-coordinate.</td>
</tr>
<tr>
<td>CD3YPixel</td>
<td>Third common destination pixel Y-coordinate.</td>
</tr>
<tr>
<td>Riders Deboarding at CD3</td>
<td>How many passengers will get off at the third destination.</td>
</tr>
<tr>
<td>PersonTripMiles Served</td>
<td>The number of trip miles served for the passengers.</td>
</tr>
<tr>
<td>DXPixel</td>
<td>Final destination pixel X-coordinate.</td>
</tr>
<tr>
<td>DYPixel</td>
<td>Final destination pixel Y-coordinate.</td>
</tr>
<tr>
<td>Arrival Time</td>
<td>Time (in seconds) of arrival at destination pixel.</td>
</tr>
<tr>
<td>ATaxi Vehicle Miles</td>
<td>Number of miles traveled by the aTaxi.</td>
</tr>
<tr>
<td>AVO</td>
<td>Average Vehicle Occupancy, calculated as the ratio of PersonTripMiles Served and ATaxi Vehicle Miles.</td>
</tr>
<tr>
<td>FIPS</td>
<td>Destination FIPS code (all 36061 for this problem).</td>
</tr>
</tbody>
</table>
the road and better traffic flow, it seems reasonable to assume a marginally higher average speed for aTaxis. This assumption is reflected in the “Arrival Time” column, which is calculated as follows:

$$\text{Arrival Time} = \text{Departure Time} + \frac{\text{aTaxi Vehicle Miles}}{15} \cdot 3600$$  \hspace{1cm} (5.8)

Looking at the highlighted trip is a telling illustration of the aTaxi service. The 3rd aTaxi departing from pixel (13,20) leaves at 4:12P.M. There are two passengers who get on at the origin. One passenger deboards at CD1 (19,31), one passenger deboards at CD2 (25,40), and there is no CD3. The aTaxi serves 20.676 person trip miles but only travels 11.673 miles. AVO is then calculated as:

$$\text{AVO} = \frac{\text{Person Trip Miles Served}}{\text{ATaxi Vehicle Miles}} = \frac{20.676}{11.673} = 1.7712$$  \hspace{1cm} (5.9)

The aTaxi arrives at its final destination pixel (25,40) at 4:59PM, a 47 minute total ride split between the two riders.

AVO is a ratio of the benefits of service over the cost. Given this definition, one must note that AVO under the current individual car ownership system would be much lower if this was the definition used. Take, for example, a parent driving a child to school or a wife picking up her husband at the airport. In this two passenger round-trip scenario, one would define the AVO to be 1.5, with only one passenger one way and two passengers the other. Using the benefits of service over cost definition, however, only one person’s place-time utility is improved in these situations: the child’s in the first and the husband’s in the second. AVO under this definition would actually only be 0.5. In an aTaxi system where the driver is removed from the equation people would presumably rarely travel unless for their own place-time utility, unless in situations such as a parent keeping a young child company or a caretaker accompanying a sick, elderly, or disabled person. Taking this fact into account means that the current individual AVO figure in the sections below is overestimated while the aTaxi AVO numbers are most likely more accurate.
5.4.5 Ride-Sharing Impact on Trips

After running the input through the code and obtaining output data as above, one can evaluate the impact on number of trips, VMT, AVO, trip length, trip duration, and fleet size requirements according to various constraints. With the implementation of this aTaxi ride-sharing service, there should be a reduction in both the number of trips made and the VMT. AVO as well as trip length and durations, however, should increase. This phenomenon will be examined for four, five, six, seven, and eight-passenger aTaxis. While the higher capacity aTaxis are somewhat unrealistic as of now, it is possible that the vehicles increase in size, and hence capacity, over time to further reduce trip miles and number of trips taken. The results below are split into two max-circuity constraints - 125% and 115% - for ease of comparison.

Max-Circuity=125%

With max-circuity at 125%, departure delay (DD) and capacity constraints are varied to find the optimal service.

Trip Length and Duration Distributions

By looking at capacity in terms of trip length and duration distributions, one can discern the optimal capacity for the aTaxi system in Manhattan. In Figures 5.17 and 5.18 are two examples (DD=120s, DD=300s) of graphs showing the various quartiles of length and duration for each capacity by departure delay. The quartile graphs for the other departure delay constraints are similar and can be found in Appendix B. These results show that four-passenger aTaxis outperform other capacities in almost every quartile. The largest jump is from four- to five-passenger vehicles, whereas there is not a substantial change between five through eight capacity vehicles. Hence, for the trip length and duration KPIs, four-capacity vehicles perform best.
Trip Lengths (Miles) and Durations (Minutes), DD = Two Minutes

Figure 5.17: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=125%, Departure Delay=2 Minutes

Trip Lengths (Miles) and Durations (Minutes), DD = Five Minutes

Figure 5.18: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=125%, Departure Delay=5 Minutes
Number of Trips, VMT, and AVO

Operating under the assumption that four capacity passenger vehicles are optimal for a 125% max-circuity constraint, the next step is to look at number of trips, VMT, and AVO under different departure delay constraints. These graphs are shown in Figures 5.19 through 5.21 below.

Looking at the number of trips for each departure delay in Figure 5.19, two minutes seems to be the ideal delay constraint for four passenger vehicles. It is important to minimize the number of trips taken while choosing the shortest possible departure delay for the convenience of riders. Three or four minutes looks optimal for higher than four-passenger vehicles, but with the above finding of four-passenger vehicles as optimal for trip length and durations, a two minute departure delay is the best constraint for MC=125% according to the “number of trips” KPI.

The VMT results in Figure 5.20 indicate that there is a mild drop between two and three minutes but not much difference between three and four minute departure delays. Given the minimal change between VMT, it is important to then choose the departure delay constraint most convenient for the passengers to minimize their travel time. In this case, the optimal delay for the VMT KPI is three minutes for four-passenger vehicles.
For most of the capacity trials, AVO improves most with a departure delay of five minutes as shown in Figure 5.21. Once again, though, there is minimal difference between AVO for four-passenger vehicles no matter what the capacity. Given how similar AVO is for all capacity vehicles, the other KPIs are more compelling when deciding the optimal service. Following this logic, the very minimal difference of VMT between capacities leaves the number of trips as the most deciding KPI. A departure delay of two minutes for four-capacity vehicles outperforms the other departure delays by the largest margin according to
the trip number standard and is the most convenient for passengers, making it the optimal service under MC=125%.

Given the optimal departure delay of two minutes, max-circuity of 125%, and four-passenger capacity, one can compare the above service to the current individual ownership system. In Table 5.4 and Figure 5.22 below, one can see the above effects of aTaxi passenger capacity on the number of trips, VMT and AVO.

Table 5.4: Current versus Optimal aTaxi Service Comparison of Trips, VMT, and AVO, DD=120, MC=125%

<table>
<thead>
<tr>
<th>Passenger Capacity</th>
<th>Number of Trips</th>
<th>VMT</th>
<th>AVO</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3,892,232</td>
<td>9,007,179</td>
<td>1.78</td>
</tr>
<tr>
<td>4</td>
<td>1,070,032</td>
<td>7,560,982</td>
<td>2.21</td>
</tr>
</tbody>
</table>

Figure 5.22: Current versus Optimal aTaxi Service Comparison of Trips, VMT, and AVO, DD=120, MC=125%

This comparison shows that as passenger capacity increases from one to four, the VMT and number of trips taken decreases dramatically (shown on the primary vertical axis), while AVO increases (shown on the secondary vertical axis). From these results one can see that the optimal MC=125% aTaxi network implemented in Manhattan with four-passenger aTaxis reduces the number of trips by about four times - an impressive improvement. On
top of that, AVO increases from 1.8 to 2.2. Hence, for a four-passenger capacity aTaxi with a departure delay of two minutes, there are 1,070,032 vehicles needed to serve the demand of the city with no repositioning strategies.

Max-Circuity=115%

Running the input data with a harsher maximum-circuity constraint of 115% shows a different set of results. While the number of trips and miles traveled will go up and AVO down due to fewer options for sharing rides, the varied constraint should decrease travel time and create a more convenient implementation for passengers on the whole.

**Trip Length and Duration Distributions**

Repeating the process above, the results below show the effects of varied departure delay constraints on the same KPIs. Below are graphs showing the different quartiles for each capacity by departure delay. Again, cases DD=120 and DD=300 are shown in Figures 5.23 and 5.24 with the other DD quartile graphs in Appendix B.

**Trip Lengths (Miles) and Durations (Minutes), DD = Two Minutes**

![Graphs showing trip lengths and durations for different capacities and delays.]

Figure 5.23: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=115%, Departure Delay=2 Minutes

These results show, similarly to the MC=125% above, that four-passenger aTaxis outperform other capacities in every quartile. The biggest jump of number of trips is from
Trip Lengths (Miles) and Durations (Minutes), DD = Five Minutes

Figure 5.24: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=115%, Departure Delay=5 Minutes

four- to five-passenger vehicles, whereas there is not much change in trip numbers between five through eight capacity vehicles.

**Number of Trips, VMT, and AVO**

Operating under the assumption that four capacity passenger vehicles are also optimal for a 115% max-circuity constraint, the next step is to look at number of trips, VMT, and AVO under different departure delay constraints. These graphs are shown in Figures 5.25 through 5.27 below.

Looking at the number of trips for each departure delay in Figure 5.25, three minutes looks like the ideal constraint for four-passenger vehicles, given the biggest fall in trip numbers occurs between two and three minutes without much change even in looser departure delay constraints.

Similar to the number of trips above, the VMT results indicate that three minutes is the ideal constraint. The biggest drop in VMT for four-passenger vehicles occurs between a two and three minute delay system. This agreement of three minutes between number of trips and VMT is in contrast to the inconsistency of optimal departure delay for number of trips and VMT performance indicators under the MC=125% case.
The largest AVO improvement, shown in Figure 5.27, is between departure delays of four and five minutes, making five minutes the optimal constraint using AVO as a KPI. The inconsistencies when using different KPIs introduces the question of tradeoff between number of trips, VMT, and AVO. While all related, it is necessary to weigh one or two of them more than the others when making a decision regarding the optimal service because of their inconsistencies. Given the cases presented for AVs in Chapter Three, the number of trips and VMT should outweigh AVO as KPIs. Because safety and the environment are
the most compelling arguments for AVs, their comparable KPIs should matter more than those that indicate less important benefits, such as convenience. A reduction in number of trips and miles traveled directly lessens the risk of crashes and pollution. While certainly playing a role in mitigating these issues, AVO is less of a direct translation to safety and the environment than the sheer number of trips taken and miles traveled.

Given this logic, four-passenger vehicles with a three minute departure delay are the optimal constraints for an aTaxi system under max-circuit of 115%. Table 5.5 and Figure 5.28 below illustrate the KPI improvements between this optimal MC=115% ATN and the current individual car ownership system.

Table 5.5: Current versus Optimal aTaxi Service Comparison of Trips, VMT, and AVO, DD=180, MC=115%

<table>
<thead>
<tr>
<th>Passenger Capacity</th>
<th>Number of Trips</th>
<th>VMT</th>
<th>AVO</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3,892,232</td>
<td>9,007,179</td>
<td>1.78</td>
</tr>
<tr>
<td>4</td>
<td>1,127,647</td>
<td>7,213,664</td>
<td>2.38</td>
</tr>
</tbody>
</table>

These results again show significant improvement over the current individual car ownership system, with lowered number of trips and VMT and a substantial rise in AVO.
Comparison of Max-Circuities

The above analysis of departure delays and vehicle capacities yields the following optimal services under each max-circuity constraint:

- **Max-Circuity = 125%**: Four-passenger vehicles with departure delay of two minutes
- **Max-Circuity = 115%**: Four-passenger vehicles with departure delay of three minutes

The next step is then to directly compare these two alternatives to decide on the optimal max-circuity constraint. Figures 5.29 through 5.31 below show each service’s performance according to the KPIs.

While MC=115% makes more trips, it outperforms MC=125% in VMT, AVO, trip length, and trip duration. In the case of a tighter max-circuity constraint, many more short trips are taken as opposed to fewer, longer trips with MC=125%. Given that the case where MC=115% maximizes AVO while minimizing VMT, trip length, and duration, it is a better service than MC=125%.

The optimal aTaxi service in Manhattan thus consists of four-passenger vehicles, has a departure delay of three minutes, and a max-circuity constraint of no more than 115% of the original straight line distance each individual would have traveled.

Figure 5.28: Current versus Optimal aTaxi Service Comparison of Trips, VMT, and AVO, DD=180, MC=115%
Fleet Size Requirements per Minute

After discovering the optimal ATN for Manhattan, it is helpful to look at fleet requirements by time of day. The graph in Figure 5.32 below illustrates the fleet requirements per...
every half hour. The minimum fleet size under this level of service is close to 15,000 at the peak between 9:00 and 9:30 A.M. with instantaneous repositioning.

Figure 5.32: Fleet Requirements by Half Hour for Optimal Manhattan aTaxi Service

This graph has a similar shape to the original individual trip departures per second. The busiest times of day are to be expected - commute to work or school, lunch, and home.
5.4.6 aTaxi Stand Placement

After generating the aTaxi output file for the optimal service (MC=115%, DD=180, Capacity=4), it is possible to match the pickup pixels to the original longitude and latitude coordinates. Each aTaxi stand is placed at the centroid of every origin pixel, as shown below in Figures 5.33 and 5.34.

![Figure 5.33: aTaxi Stands Downtown](image1)
![Figure 5.34: aTaxi Stands Uptown](image2)

The densities of each stand can be compared to the individual trip density heat map in Figures 5.35 and 5.36 below. The individual trip densities match well to the aTaxi stands’ demand concentrations.
Figure 5.35: Individual Trips

Figure 5.36: aTaxi Stand Trips
5.4.7 Cost per Mile and aTaxi Savings

From the AVO results, one can also analyze the cost savings of the autonomous ride-sharing network. The cost of an aTaxi ride will be lower than that of a conventional cab ride because there will be no driver. It could also, depending on the commuter’s annual driving mileage and car occupancy, be less than owning a vehicle. BCG’s autonomous vehicle report ran a case study on a New York City “robo-taxi” system, showing the cost per passenger mile for each type of vehicle. It found that the cost of conveying one passenger one mile by aTaxi would be 35% less than doing so by conventional taxi at the average occupancy rate of 1.2 passengers. The report also found aTaxis to become competitive with mass-transit at an occupancy rate of two passengers.\[43\] Their findings are pictured in Figure 5.37 below.

![Figure 5.37: Cost Per Passenger Mile by Vehicle Type](image)

Table 5.6: Current versus Optimal ATN Cost Savings

<table>
<thead>
<tr>
<th>Trip Miles</th>
<th>aTaxi Trip Miles</th>
</tr>
</thead>
<tbody>
<tr>
<td>9,007,179</td>
<td>7,213,664</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cost per Mile</th>
<th>aTaxi Cost per Mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1.20</td>
<td>$0.90</td>
</tr>
</tbody>
</table>

| Cost             | $10,808,615         | $6,492,298          | $4,316,317 annual savings |

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The cost per passenger mile in New York City of aTaxis decreases as the average occupancy grows. The optimal ride-sharing system implemented above - with four-passenger aTaxis, a departure delay of three minutes, and a max-circuity constraint of 115% - severely reduces the cost per passenger mile. It is estimated that a four-passenger aTaxi with an AVO of 2.4 has a cost of about $0.90 per mile. Table 5.6 above details the potential annual cost saving of this aTaxi system, assuming BCG’s costs per mile.
Chapter 6

Conclusion

6.1 Summary

This thesis examines the current landscape of autonomous vehicles in both the United States and China, makes the case for them in appropriate environments, argues that AV implementation will eventually take the form of ride-sharing services within urban centers, discusses adoption in China, and, finally, models the optimal autonomous taxi service for Manhattan using synthesized individual trip data. The overall message regarding AVs from current literature and articles examined in Chapter Two is that AVs are a certainty, given the important benefits they bring to improved safety, environment, congestion, and efficiency. This is tempered by the fact that while the technology has made large strides it is not perfect - as evidenced by the multiple crashes - and regulation has yet to catch up. Chapter Three, “The Case for Autonomous Vehicles,” stressed the importance of AVs in mitigating traffic-related deaths, pollution from vehicle emissions, improvement of traffic flow, and causing increased efficiency. Chapter Four, “Implementation in China,” then discussed AV integration in the world’s most populous country, evaluating its approach toward implementation, advantages in adoption, and possible challenges it will face in the process. This chapter argued that China - with the largest population and serious environmental problems - has some of the most compelling reasons in the world to adopt AVs. China’s approach to the AV market will come from their deep learning and artificial intelligence
expertise. Their corporate culture and close ties to the government should allow for earlier AV rollouts and, hopefully, governmental cooperation.

Chapter Five programmatically modeled one solution to the ATN implementation problem within Manhattan. Using synthesized individual trip data this chapter analyzed the transportation demand landscape within Manhattan, looking at trip type, distance, and time distributions and densities. The aTaxi algorithm, using this data as input, placed individuals into an SPT-based ATN, varying departure delay, max-circuitry, and passenger capacity constraints. By comparing the different ATNs according to key performance indicators - number of trips taken, vehicle miles traveled, average vehicle occupancy, and trip lengths and durations - the chapter identified the optimal service: four-passenger vehicles, three common destinations, a three minute departure delay, and 115% max-circuitry constraint. This was found to reduce the number of trips by a factor of about 3.5, VMT by 1.25, increase AVO from 1.8 to 2.4, and save approximately four million dollars annually in cost per passenger mile.

6.2 Future Work

Because AVs are a relatively new field of technology and study, the landscape is ever-changing. Companies make developments, governments modify regulation, and society shifts its views quickly. There will be many adjustments needed before an ATN can actually be implemented in a city, causing necessary further study and observation of the dynamic subject.

In terms of the programmatic implementation in Chapter Five, there are many ways to improve the analysis of an optimal ATN. First, the common destinations constraint could be changed from three stops to either more or fewer. It would be useful to vary that restriction to see its effect on the KPIs. Additionally, evaluating different taxi repositioning strategies to minimize the fleet requirement would give a more accurate sense of practical ATN implementation. It would also be helpful to look at real trip datasets, whether they consist of Uber rides, taxicabs, or a combination of both. While the synthesized data in this thesis gives a useful sense of a typical weekday, real data could improve the execution
and analysis. And, finally, this problem is not limited to Manhattan - it can and should be extended nationwide and to other cities around the world.
Appendix A

aTaxi Ride-sharing Algorithm

Pseudocode

Algorithm 1 aTaxi Algorithm
1: for all input trip files do
2:     read in files
3:     make person trips array
4:     make person trips array
5:     make aTaxi array
6:     initialize first taxi in line
7:     initialize last taxi in line
8:     for all individual trips do
9:         if person and current fleet are leaving from the same pixel then
10:            for all waiting taxis do
11:               if departure time of person > aTaxi departure time then
12:                  departure count = departure count + 1
13:                  send taxi and update aTaxi Vehicle Trip File
14:                  update last taxi in line
15:            end if
16:        end for
17:        initialize success \(\triangleright\) the finding of an appropriate aTaxi
for all waiting taxis do
    if taxi is under capacity then
        if person’s destination = aTaxi’s CD1 then
            update riders at departure
            update person trip miles served
            update riders getting off at CD1
            success = 1
        else if person’s destination = aTaxi’s CD2 then
            repeat the above
        else if person’s destination = aTaxi’s CD3 then
            repeat the above
    end if
end for
if success = 0 then
    for all waiting taxis do
        if taxi is under capacity then
            if CD2 is null then
                calculate leg distances \(\uparrow\) there are three legs
                calculate route distances \(\uparrow\) there are two routes
                if route 1 < route 2 max circuity < 1.25 then
                    update CD2 info
                    success = 1
                else if max circuity < 1.25 then
                    update CD1 info
                    change riders getting off at CD1 to CD2
                    success = 1
                end if
            else if CD3 is null then
                calculate leg distances \(\uparrow\) there are six legs
            end if
        end if
    end for
calculate route distances \(\triangleright\) six possible routes

if shortest route and max circuity \(<\ 1.25\) then

update info necessary

success = 1

end if

end if

end if

end for

if success = 0 then \(\triangleright\) if all else fails, make a new taxi

if there is only one taxi waiting and that taxi is empty then

add passenger

end if

end if

else \(\triangleright\) person is not leaving from the same pixel so depart all taxis and reinitialize them to a new origin pixel

for all waiting taxis do

departure count = departure count + 1

copy info to aTaxi Vehicle Trip File

end for

end if

\(\triangleright\) depart all the taxis now that individuals have been placed

if there is only one taxi and it is empty then

for all waiting taxis do

depart them

update info

end for

end if

end if

write aTaxi output file
Appendix B

aTaxi Ride-sharing Graphs

B.1 Max-Circuity 125%

Figure B.1: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=125%, Departure Delay=3 Minutes
Trip Lengths (Miles) and Durations (Minutes), DD=Four Minutes

Figure B.2: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=125%, Departure Delay=4 Minutes

B.2 Max-Circuity 115%

Trip Lengths (Miles) and Durations (Minutes), DD = Three Minutes

Figure B.3: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=115%, Departure Delay=3 Minutes
Trip Lengths (Miles) and Durations (Minutes), DD = Four Minutes

Figure B.4: Quartiles of Trip Lengths and Durations by Capacity, Max-Circuity=115%, Departure Delay=4 Minutes
Bibliography


[23] Changan Automobile. Changan’s Autonomous Sedan Hits the Road, April 2016.


[34] KPMG. Self-driving cars: The next revolution. 


[52] Schoettle, Brandon and Sivak, Michael. Transportation Research Institute, University of Michigan, July 2014.


