CHANGING CONCEPTS OF TRAFFIC WITH AN INCREASING PERCENTAGE OF AUTONOMOUS VEHICLES

BY

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THESIS

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Abstract

The development of autonomous vehicles (AVs) has advanced at an unprecedented pace in the past decade. While the public have high expectations of how it would reshape future traffic, it remains unclear how people will interact and respond to a gradual introduction of AVs. On the other hand, algorithms of AVs may be adjusted to adapt to human's varying behavior, resulting in a feedback loop. Therefore, this paper provides experimental simulations on how an increasing percentage of AVs and change in manual driving behavior may affect traffic. In particular, four types of traffic are focused, including single lane, double lane with left lane as fast lane or overtaking lane, and controlled intersection traffics. Despite making simplified versions of traffic, this paper seeks to make simulations close to reality by making reasonable assumptions and simplifications. To quantify different aspects of traffic usage efficiency, five parameters are measured, including throughput, minimum, maximum, average, and standard deviation of travel time, with additional parameters measured for specific simulations. The results show that when the percentage of AVs is below a certain threshold (40%), its introduction has mixed impacts on the traffic, while its benefits become more significant when its percentage rise above the threshold, indicating qualitative differences in traffic behavior as a function of the percentage of AVs. Compared to full AV, even minor presence of manual-driving vehicles has huge impact on the traffic in some circumstances.

Keywords: autonomous vehicles, traffic simulation, feedback loop

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Chapter 1

Introduction

As autonomous vehicles emerged and became widely popular in the past decade, they also led to high expectations of how they could make transportation safer and more efficient. Compared to humans, AVs are designed with more processing power to analyze surrounding information, and faster response time. As a result, AVs are expected to enhance passenger safety and reduce traffic congestion by decreasing the necessary safety buffer. In addition, a traffic network can facilitate communications between AVs, enabling preemptive adaption to events ahead of time, such as traffic accidents and congestion. AVs can also share information with traffic network and optimize road usage. Aside from the clear advantages of applying automation in traffic, it is unclear to what extent it would reshape current traffic. For instance, when AVs fully penetrate the market, can networking traffic replace traffic signals? When AV technology fully matures, can the front row fit three passengers by removing the driving wheel?

Since individual human drivers respond to an increasing penetration of AVs differently, it can lead to unforeseen side effects. With the knowledge that AVs will always follow traffic rules, manual drivers can drive more recklessly, knowing that they can reach the destination faster and safer, despite making the entire traffic less efficient. This same reasoning applies to pedestrians who can gain higher priority when crossing intersections. The underlying selfishness of human behaviors may be an important factor that hinders the wide usage of autonomous vehicles in the future. This paper explores traffic simulations under various scenarios with an increasing percentage of AVs and the corresponding effect on manual driving behavior.

Chapter 2

Literature Review

Studies on influences of consumers' intention to adapt to AVs reveal that their perspectives have huge impacts on their market penetration. In a recent survey (Tussyadiah, Zach & Wang, 2017), respondents show that adverse attitude towards AVs is associated with its perception of dehumanizing, and AV developers are recommended to convey to the public that AVs can create new job opportunities. Trust in AVs takes years to build up, because in the current generation, driver expectations are strongly connected to their control over the vehicle (Abraham et al., 2016). Acceptance of AVs is also relevant to socio-demographic profiles, as studies show that AV enthusiasts are typically male, young, highly educated and live in urban areas (Nielsen & Haustein, 2018). The demand of AVs and other in-vehicle technologies can potentially increase for the aging population (Yang & Coughlin, 2014).

In the era of automation, AVs raise the concern of humans being killed by machines. In 2013, 1.25 million people were killed in road traffic (World Health Organization, 2015), yet humans continue to operate vehicles despite tragedies happening at an alarming rate. On the other hand, traffic accidents involving AVs quickly draw public attention. On May 7th, 2016, Joshua Brown became the first person to be killed in a vehicle set to auto-pilot mode, and Google's search frequency for "Tesla Car" peaked in its aftermath (Henschke, 2019). On March 18, 2018, Elaine Herzberg marked the first pedestrian fatality by an AV. Friends of the victim claimed that Uber should shut down, and Uber eventually removed their testing vehicles under pressure (Esposito, 2019). When AV is first introduced to the society, it takes a long time to establish trust among public. Yet, it is quickly destroyed when accidents occur, despite its intention to reduce traffic accidents.

The gradual integration of AVs also spark debate of who should be held legally responsible when AVs are involved in traffic accidents. A study (Hevelke & Nida-Rumelin, 2019) presents three options, each with its own advantages and flaws. First, manufactures seem to be the obvious solution because they should be responsible for their defective products. However, the liability burden diminishes the incentive for manufactures to make marginal safety improvements (Marchant & Lindor, 2012). Second, drivers may be held responsible for failing to intervene when necessary. The aviation industry is one of the most noticeable benefactor of auto-piloting. When automation was first introduced, pilots shifted their focus from manual control to monitoring and supervising aircraft automation (Wolf, 2016). Nonetheless, if drivers are obligated to intervene when needed, AVs also lose much of its utility. Third, drivers do not have legal duty to intervene when necessary, but are morally responsible when accidents occur, because their operation of the vehicle imply their acceptance and acknowledgement of the potential risks. This solution can be justified by holding all AV users collectively responsible, while encouraging manufactures to enhance safety of AVs (Hevelke & Nida-Rumelin, 2019).

Almost every novel innovation faces the challenge of adapting to societal conventions. AVs are no exception, and can be even harder due to the complexity of human behavior. While AVs are expected to avoid traffic accidents, current AV tests yield an adverse result. The primary factor is that the driving patterns of machines deviate from what most drivers today expect (Tavassoli et al., 2019). Since machines tend to strictly follow rules without exceptions, it may result in contradictions with conventional traffic behaviors (Steinke, Ulbrich, Goehring & Rojas, 2018). AVs have to express intentions, consider intentions from other road agents, and adjust their behavior accordingly (Vinkhuyzen & Cefkin, 2016). Another challenge is to integrate software components while taking into account of how errors propagate through the pipeline (McAllister et al., 2017). Efforts have been made to mitigate this issue, such as hierarchical game-theoretic planning (Fisac et al., 2018), which takes advantage of high-performance parallel computing hardware to enable safe and efficient interactions with human drivers.

Chapter 3

Methods

3.1 Model building

A model was built to explore the effects of AVs on traffic. The simulations included AVs and manual driving vehicles with different ratios, and variable manual driving behavior. In the following simulations, one of the best-selling vehicles in the US, Toyota Camry, was selected as the model vehicle with length of 4.4 meters. The vehicle class type includes the following attributes in all simulations. Additional attributes for specific simulations are specified in the following sections.

- id: The identification number for each simulated vehicle, starting from 0.
- *pos*: The current position of the vehicle (m). This attribute only recorded how much distance the vehicle has traveled, and the lane in which the vehicle was travelling was determined by the global data structures in which the vehicle object belonged to.
- speed: The current speed of the vehicle (m/s).
- comf: The comfortable speed of the vehicle (m/s). This value was constant for autonomous vehicles at 16.67 m/s (or approx. 37 mph), while the comfortable speed for manual vehicles was simulated from a normal distribution $\mathcal{N}(16.67, \sigma^2)$ with a variable standard deviation.

- acc: The acceleration of the vehicle (m/s^2). This value was constant for autonomous vehicles at 3.33 m/s^2, while the acceleration for manual vehicles was simulated from a normal distribution $\mathcal{N}(3.33, \sigma^2)$ with a variable standard deviation. Even though the model vehicle was capable of accelerating at an even faster speed, most drivers would not be driving in such behavior. Furthermore, constantly driving with full acceleration would cause huge discomfort for passengers. The deceleration of the vehicle was the negative value of the acceleration.

- length: Length of the vehicle (m). This value is 4.4 for all vehicles.

- type: Dummy variable for vehicle type. 0 for autonomous vehicles, 1 for manual vehicles.

The model was built under the assumption that manual drivers deviate in their comfortable speed, and how recklessly they drive the vehicle, modeled as the range of acceleration. These parameters were generated from a normal distribution, with the mean same as that of AVs, and the standard deviation ranging from 0.00 to 0.20. To quantify the variability of manual driving behavior, let $SDMB$, denote the standard deviation of manual driving behavior, which included acceleration and comfortable speed.

Nonetheless, it was impossible for humans to strictly behave under these rules. Yet, assumptions and simplifications were required for simulations, and they could be useful when designing algorithms for AVs. The following list some driving behaviors in reality that may deviate from the simulation:

1. Manual drivers do not behave under a normal distribution. Additional factors, such as weather, location and traffic flow all contribute to manual driving behavior.

2. AVs require a shorter safety distance. Without the knowledge that the vehicle behind is an AV, a manual driver may feel uncomfortable with the vehicle behind being so close, and be pressured to drive faster. Even if the driver knew the vehicle behind was an AV, he or she may still feel uncomfortable because the safety distance is shorter than expected.

3. AVs are expected to have a more consistent and predictable behavior compared to manual drivers. Yet, slight deviations should still exist among AVs.

4. In single lane traffic, vehicles behind a significantly slow vehicle would likely signal or pressure the vehicle to drive faster, instead of waiting patiently.

5. In double lane traffic where the left lane is the overtaking lane:

    - When a vehicle initiates an overtake, the lane switch does not happen instantly.
    - Drivers overtake multiple vehicles in certain occasions, such as the driver has a significantly high comfortable speed, or there is not adequate safety distance for the vehicle to merge back to the right lane.
    - Drivers make spontaneous decisions of whether it is safe to initiate an overtake, instead of strictly following the rules specified in the simulation. The algorithm can however be implemented in AVs.
    - In states where the left lane is used only for overtakes, it rarely happens in reality. Faster vehicles may initiate an overtake and remain in the left lane for a long duration. In many locations, people simply consider it a double lane traffic with blurry distinctions between the two lanes.

6. In double lane traffic where the left lane is the fast lane:

    - Lane switch still occur, even though not all of them are intended to be an overtake.
    - There does not exist a clear threshold in which vehicles have to drive on the left lane when above. Similarly, many people simply consider it a double lane traffic, where a faster vehicle may reach the destination faster by making multiple lane switches.

7. In an controlled intersection:

    - The simulation does not include the time period between the traffic light of one direction turns yellow, and the that of the other direction turns green. Changing the time duration of the cycle may yield interesting results.
    - Vehicles and pedestrians were added to the simulation at low density to avoid deadlocks. In reality, deadlocks rarely happen because social conventions allow traffic agents to communicate and

figure out who should go first. For example, a driver may wave his hand to grant a pedestrian lane priority. The pedestrian may nod back to show his acceptance, appreciation and acknowledgement of the lane priority. It also implies that AVs may need to emit and accept external signals to communicate its intentions with the outside world, unless all traffic agents are networked (Networking all AVs may be viable, but networking pedestrians will raise technical challenges and privacy concerns).

- Pedestrians have huge impact on the traffic because typically take a longer time to finish their intersection travel compared to other agents. When pedestrian density is high and they travel whenever possible, pedestrians tend to gain huge lane priority because before the first pedestrian reaches the other side, a second pedestrian may have entered the lane. As a result, pedestrians tend to travel in clusters when pedestrian density is high.

3.2 Single lane traffic

In the single lane simulation, vehicles travelled without overtaking while maintaining an appropriate safety distance with the vehicle in front. Recommended safety distances (Queensland Government, 2016) were interpolated with a polynomial as a function of speed. Dry roads were assumed in the simulation. The recommended safety distances were as follows:

Speed (kph)	40	50	60	70	80	90	100	110
Safety Dist. (m)	26	35	45	56	69	83	98	113

Using regression models, an appropriate polynomial function was derived using ANalysis Of VAriance (ANOVA) tests between three models for manual driving vehicles. Let x, y denote the speed and safety distance, and k denote constant. The three models were:

$$m_1 : y = ax + k \tag{3.1}$$

$$m_2 : y = ax^2 + bx + k \tag{3.2}$$

$$m_3 : y = ax^3 + bx^2 + cx + k \tag{3.3}$$

The ANOVA results were:

$$\text{ANOVA}(m_1, m_2) = 0.000009687$$

$$\text{ANOVA}(m_2, m_3) = 0.1004$$

At 0.05 significant level, m_2 was selected. In all simulations, the following equation would be used to ensure enough safety distance with the vehicle in front for manual driving vehicles.

$$y = 0.005774x^2 + 0.385119x + 1.232143 \tag{3.4}$$

or in meters per second (figure 3.1)

$$y = 0.074829x^2 + 1.386429x + 1.232143 \tag{3.5}$$

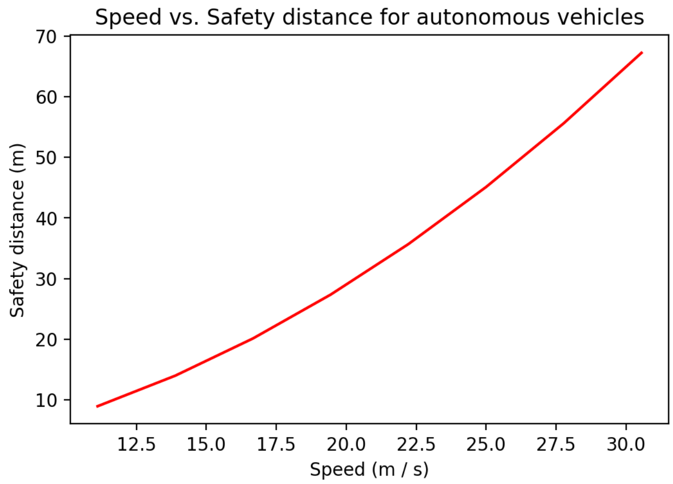


Figure 3.1

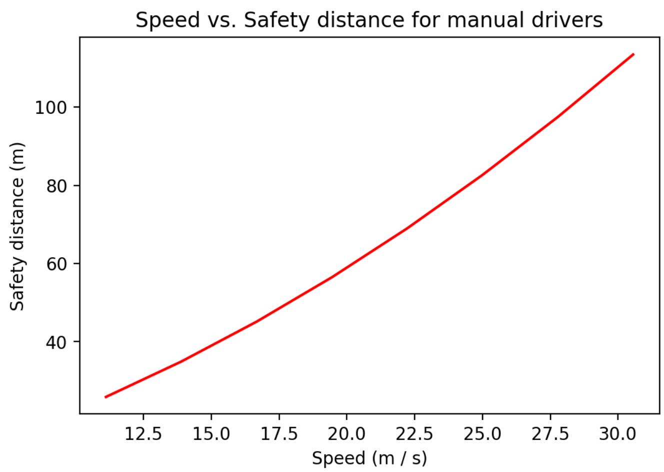


Figure 3.2

Similarly, ANOVA tests were performed on the recommended safety distance for AVs, which were assumed to have instantaneous reaction time. The recommended safety distances without reaction distance were as follows:

Speed (kph)	40	50	60	70	80	90	100	110
Safety Dist. (m)	9	14	20	27	36	45	56	67

Let m_1, m_2, m_3 denote the same three models above. The ANOVA results were:

$$\text{ANOVA}(m_1, m_2) = 0.000002545$$

$$\text{ANOVA}(m_2, m_3) = 0.2592$$

At 0.05 significant level, m_2 was selected. In all simulations, the following equation would be used to ensure enough safety distance with the vehicle in front for AVs.

$$y = 0.0054762x^2 + 0.0119048x - 0.3214286 \tag{3.6}$$

or in meters per second (figure 3.2)

$$y = 0.070971x^2 + 0.042857x - 0.321429 \tag{3.7}$$

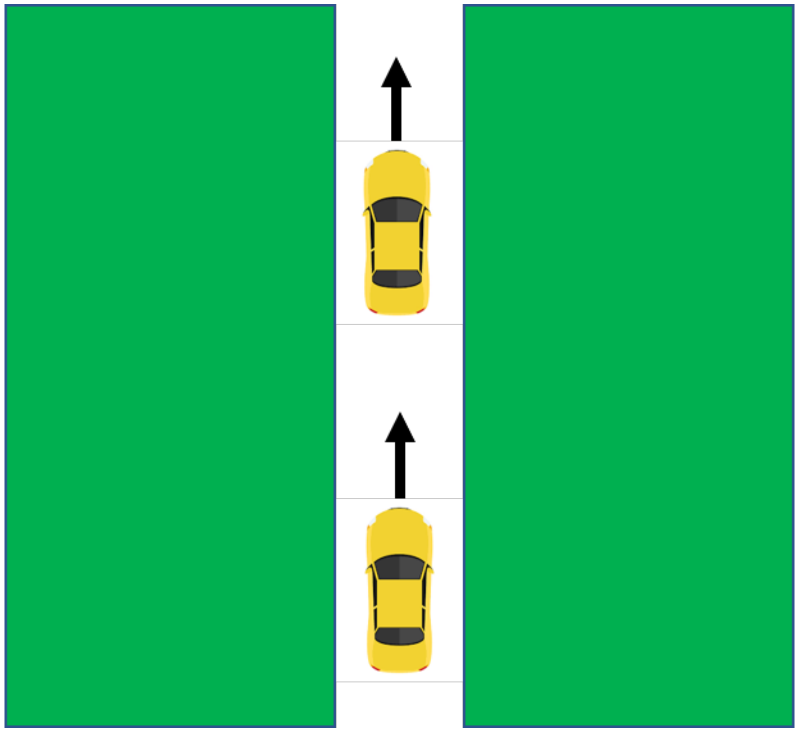


Figure 3.3: Single lane simulation

Vehicles travelled in a single lane without any type of overtaking, as shown in figure 3.3. Vehicles were assumed to have the tendency to travel at their comfortable speeds whenever possible, and the road was implemented as a queue. A new vehicle would be added to the queue when the vehicle last added to the queue passed a certain threshold. The threshold was dependent on whether the vehicle added was manual driven or autonomous. In each simulation, vehicles traveled 1000 meters and lasted for 1200 seconds. When a vehicle finished the travel, it would be removed from the queue. If a vehicle detected that there were no vehicles in front, it would accelerate or decelerate at its comfortable speed.

3.3 Double lane traffic with fast lane

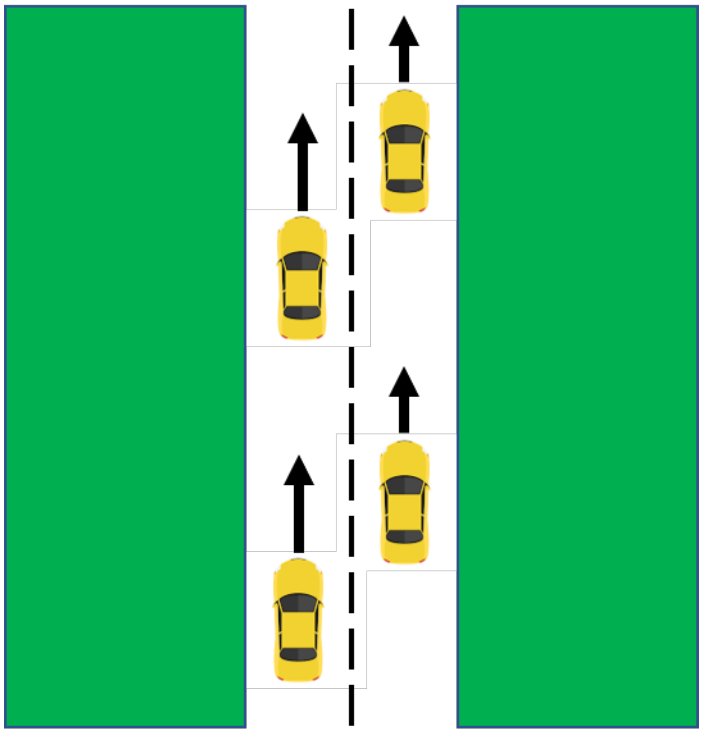


Figure 3.4: Double lane simulation with fast lane

In other states, the left lane could be used as fast lane. In the simulation, vehicles were prohibited from switching lanes (figure 3.4). Vehicles were first assigned to a designated lane based on their comfortable speed, and the way they were added to the queue was the same as that of the single lane simulation. Lane assignment was as followed:

- Manual driving vehicles: Assigned to the fast lane if comfortable speed was above average, and assigned to the right lane otherwise
- Autonomous vehicles: Randomly assigned to the fast lane or slow lane with the same probability

The move of each lane was independent with respect to the other lane, and its algorithm was the same as that of the single lane simulation.

3.4 Double lane traffic with overtaking lane

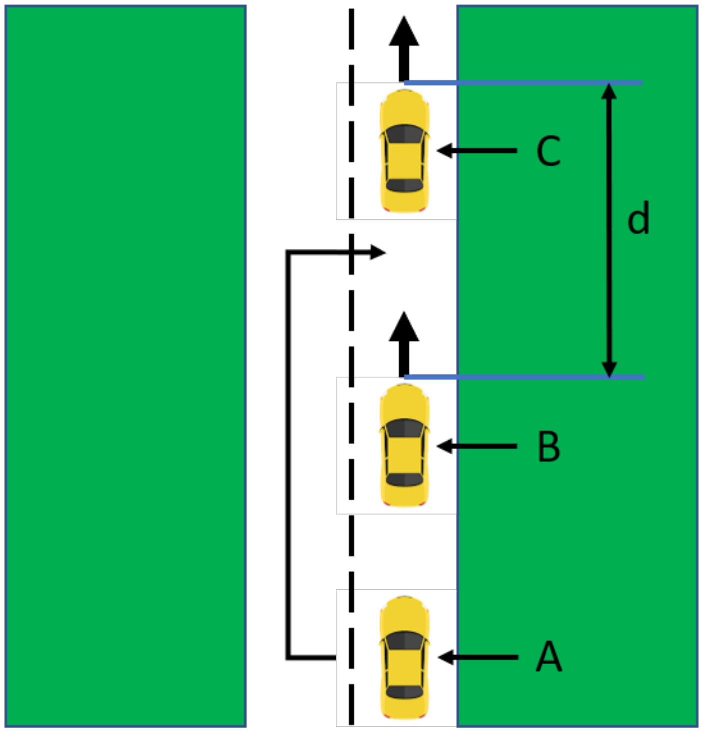


Figure 3.5: Double lane simulation with overtaking lane (overtaking phase)

In a growing number of US states, drivers are required to drive in the right lane, and use the left lane only for overtaking (Wickert, Matthiesen, & Lehrer, 2018). These states account for roughly half of the US population, and included populous states such as California and New York. This simulation consisted of two lanes, where the right lane was the normal driving lane, and the left lane was the overtaking lane, as shown in figure 3.5. Throughout the simulation, vehicles were added to the right queue the same way they were added in the single lane simulation. In each simulation, vehicles traveled 1000 meters and lasted for 1200 seconds.

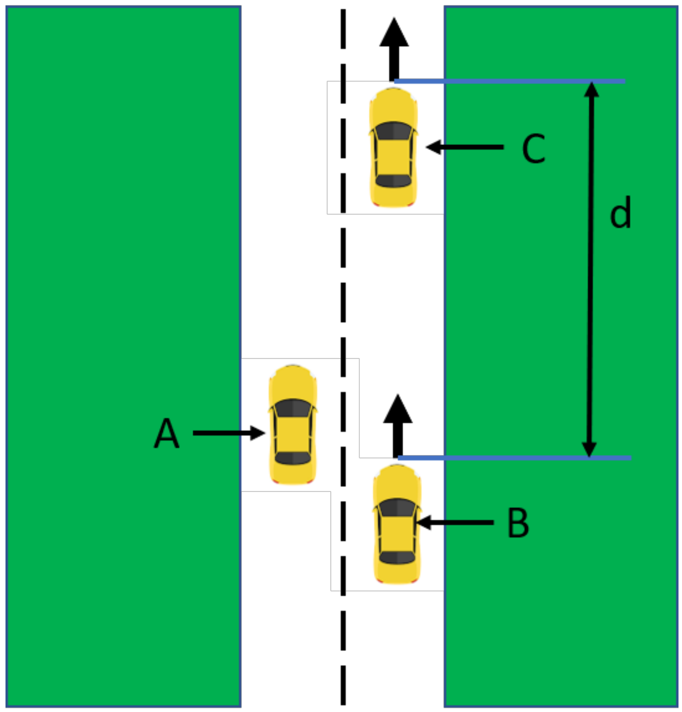


Figure 3.6: Double lane simulation with overtaking lane (merging phase)

In each time step, each vehicle A was checked whether the following conditions were satisfied:

1. A's comfortable speed was less than 0.8 times of its comfortable speed
2. A's comfortable speed was 20% more than B's comfortable speed
3. A had travelled over 60 meters
4. d was greater than the safety distance required for the comfortable speed of A and B
5. There were no vehicles currently overtaking B

If all the conditions were met, A would initiate a overtake and was moved to the overtaking lane instantly. It also recorded the vehicle it overtook, and sought to merge back to the right lane when d enabled adequate distance for A and B maintain a safety distance, as shown in figure 3.6.

3.5 Intersection

Intersections required special consideration in simulation due to their complex nature. Vehicles could behave differently when they saw a yellow light, and the traffic flow also differed among the duration of the green light. Therefore, the simulation focuses on the time period where vehicles and pedestrians were always allowed to move freely in the North–South direction, while the traffic lights for the East–West direction were constantly red.

In previous simulations, vehicles were added whenever possible to show the maximum throughput of the traffic. The algorithm also implied that gaps between each vehicle was minimized with only enough distance for safety, which was not enough for vehicles to turn, and would result in deadlocks. As a result, vehicles and pedestrians were added to the queues at low frequency. It was assumed that 15% of vehicles turn, and 85% of vehicles go straight. Vehicles had an equal probability of turning left or right. Due to a different method of adding vehicles, throughput became meaningless and was therefore eliminated from the statistics.

Each lane was 215 meters long, which included 100 meters before entering, 15 meters during travelling, and 100 meters after leaving the intersection. The lane and median were both 3 meters wide. Additionally, vehicles had the following considerations:

- *direction*: recorded whether the vehicle's intended route was to a turn
- *require*: the threshold distance required for the vehicle to decelerate from its comfortable speed to 30 (mps)
- *slow*: whether the vehicle was required to continue decelerating and stop at the median. The value was only meaningful for vehicles with *direction* of 0

Despite the fact the vehicles were allowed to travel at the same speed when making a turn in intersections, it was assumed that drivers would travel slower for safety reasons. The change in behavior could also be observed in most intersections. Therefore, a cap of 8.33 (mps) was implemented on the speed of travelling through the intersection when turning. The simulation includes four driving lanes and two pedestrian crossings as shown in the following graph:

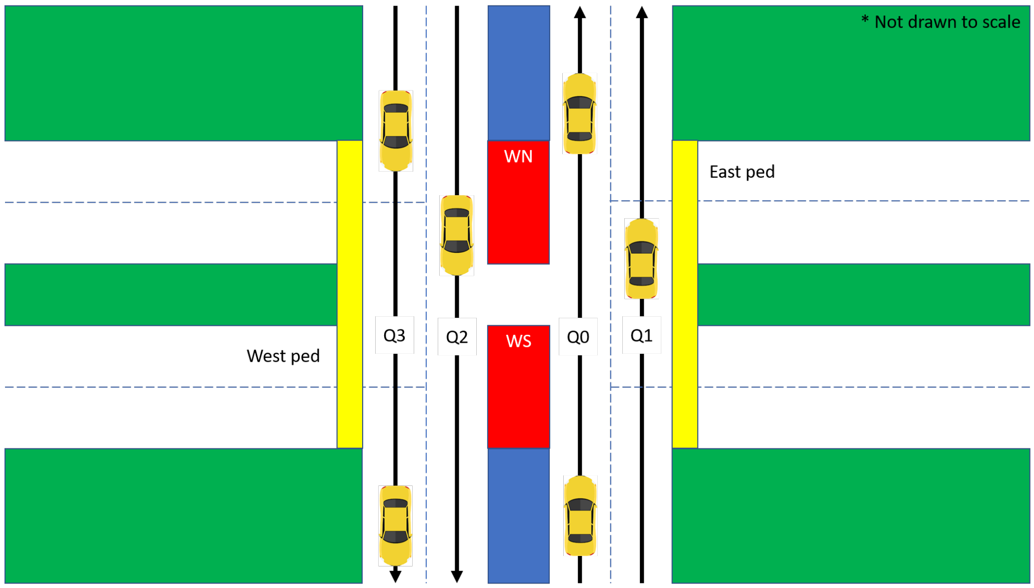


Figure 3.7: Intersection traffic simulation (Straight)

The intersection simulation for vehicles going straight was shown in figure 3.7. In $Q0$ and $Q2$, vehicles were allowed to go straight or turn left, but not right. In $Q1$ and $Q3$, vehicles were allowed to go straight or turn right, but not left. Vehicles were assumed to be in the correct lane before they enter the simulation range. In both East and West ped, pedestrians could travel in both directions. "WN" and "WS" stand for the North and South waiting medians, in which left-turn vehicles would always pass.

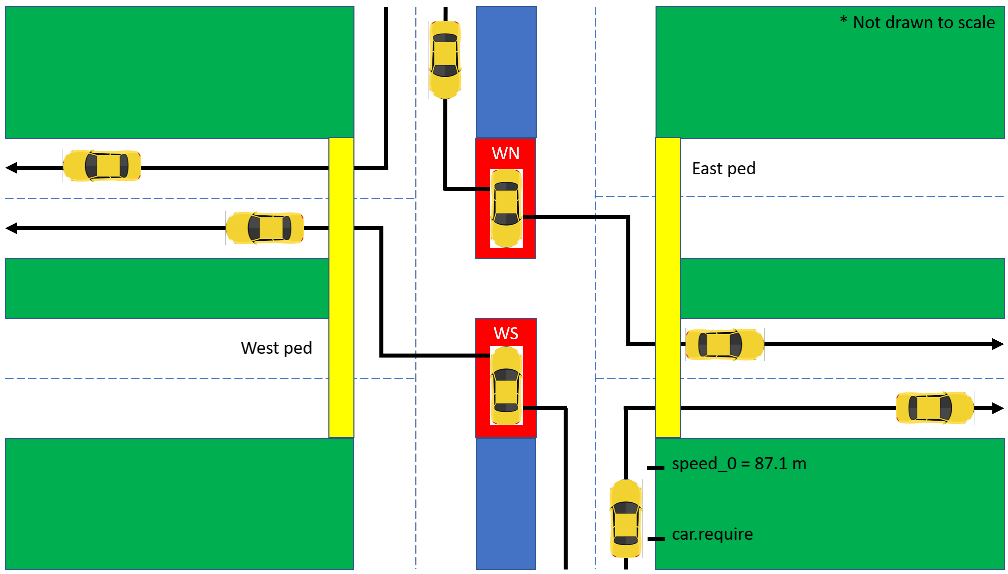


Figure 3.8: Intersection traffic simulation (Turn)

The intersection simulation for vehicles turning left or right was shown in figure 3.8. Vehicles had in the following behaviors:

- Straight: The vehicle share the same behavior with vehicles in the single lane simulation, in which it would maintain a specific safety distance with the vehicle in front, depending on its travelling speed.
- Left turns: Each vehicle had its distance threshold to start decelerating to 30 m/s, depending on its comfortable speed. Before the vehicle passed the threshold, its behavior was identical to a vehicle travelling straight. Vehicles started to decelerate when it reached the threshold, and when it reached $speed_0$, it would detect whether it was safe to pass at the designated speed (8.33 m/s). This decision depends on the traffic of both driving lanes and the pedestrian crossing in the opposite direction. For example, in Figure 3.8, whether it is safe for a vehicle on $Q0$ to make a left turn was dependent on $Q2$, $Q3$, and West ped.

If the vehicle detected any vehicles or pedestrians, its *slow* attribute would be activated, which signified that the vehicle would continue to decelerate until its speed reached the intersection. Otherwise, the vehicle would cross the intersection at the speed of 8.33 m/s. When a vehicle with *slow* activated reached the intersection, if the waiting median was not occupied, it would switch to the waiting median to allow vehicles behind to pass. Otherwise, it would stay at the same lane, potentially blocking vehicles afterwards. It would then wait until it was safe to turn.

When a vehicle initiated a turn, it would send a signal which served to prevent pedestrians on the opposite side from crossing for a 3 seconds. If the vehicle was designated as slow, the signal would last for an additional second.

- Right turns: Right-turn vehicles followed a similar plan with two differences:
  - it checked only its pedestrian crossing on the same side, which would be its only obstacles.
  - when a turn was initiated, the signal to prevent pedestrians from crossing was 1.5 seconds, with an additional 0.5 second if the vehicle's *slow* attribute was activated. The signal time was shorter because the travel distance was shorter than left-turns.

Chapter 4

Results

4.1 Single lane traffic

Figure 4.1 showed the time taken for vehicles to finish the travel under 10% of $SDMB$ and 50% of AVs, ordered by time of arrival. It could be observed that the travel time of each vehicle was heavily influenced by its preceding vehicle. To be more specific, for every vehicle v, if its comfortable speed was higher than that of its preceding vehicle, it would travel at a speed lower than its comfortable speed throughout most of the travel. When its preceding vehicle finished the travel and was removed from the queue, v could travel back to its comfortable speed, but only for a short amount of time. This explained the slight decrease of travel time of two consecutive vehicles. On the other hand, if the comfortable speed of v was lower than that of its preceding vehicle, it would travel at his comfortable speed, while increasing the gap in front over time. This explained the occasional increases when a vehicle traveled slower than its preceding vehicle.

Each combination of $SDMB$ and AVs were simulated 100 times, including throughput and average, minimum, maximum, standard deviation of time taken. The combinations were as followed:

$$c = \{(p, s) \mid p \in \{0, 0.1, 0.2, ..., 1.0\} \text{ and } s \in \{0.01, 0.02, ..., 0.20\}\} \tag{4.1}$$

These combinations were used for all the remaining simulations, with possibly additional statistics recorded. With the results averaged, the following results were obtained:

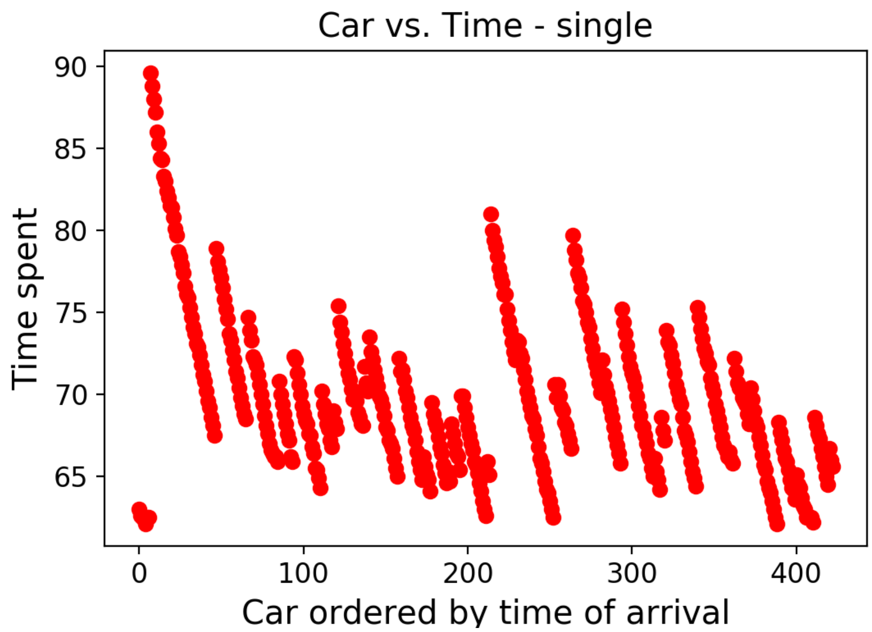


Figure 4.1: Single lane single simulation

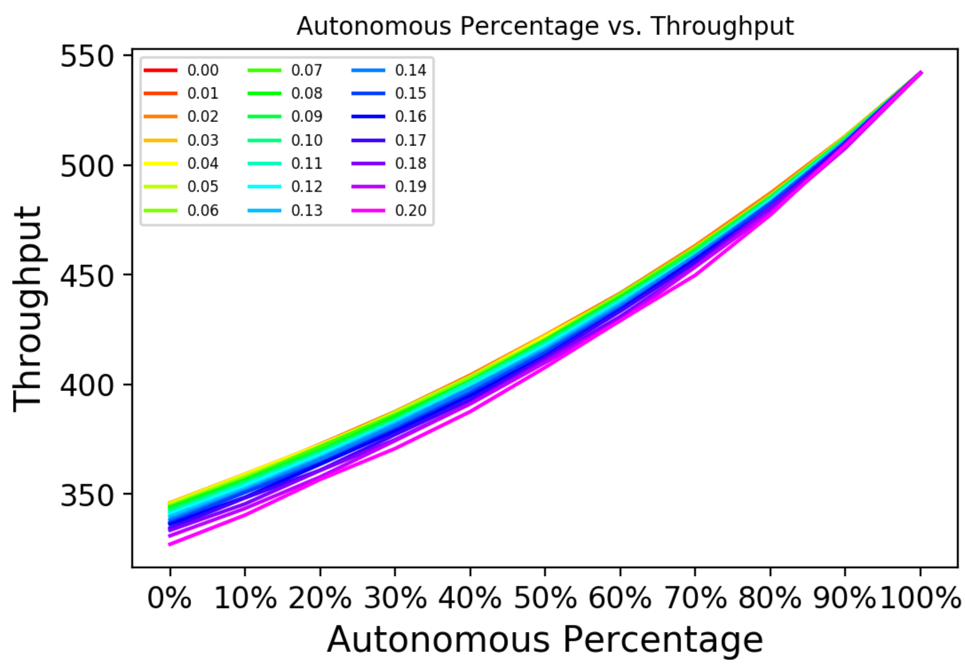


Figure 4.2

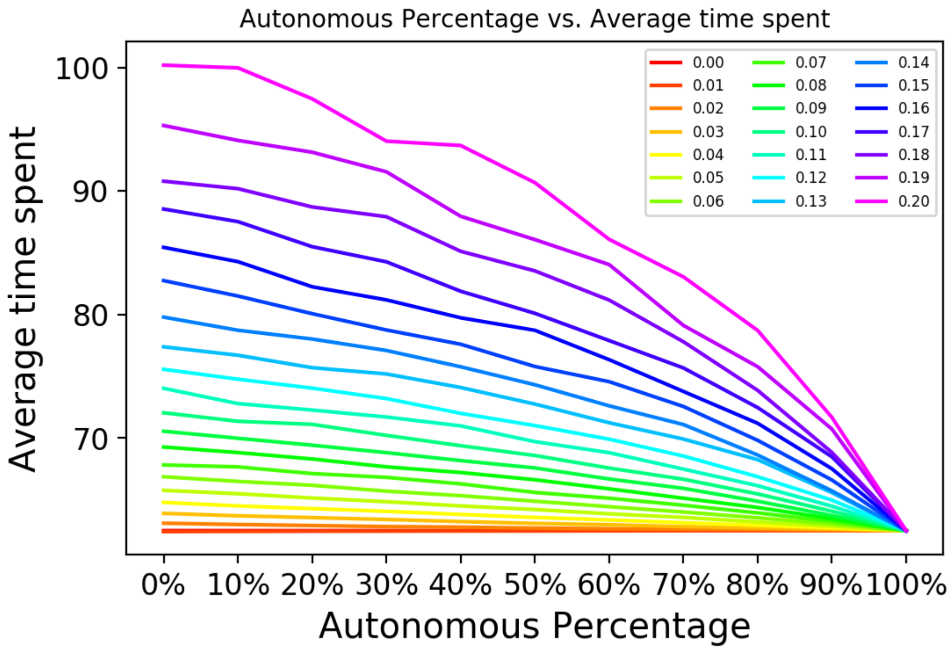


Figure 4.3

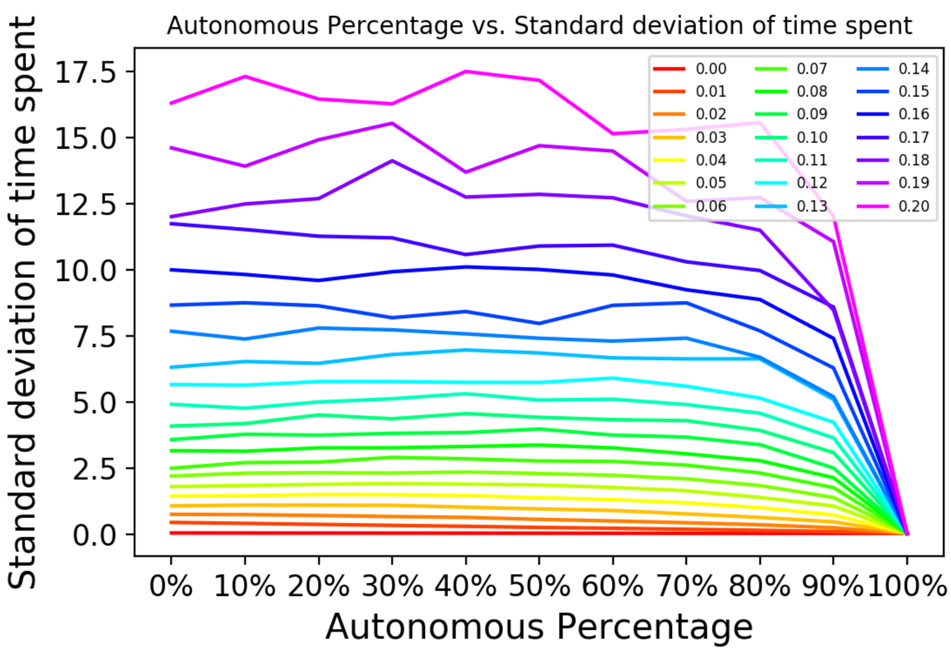


Figure 4.4

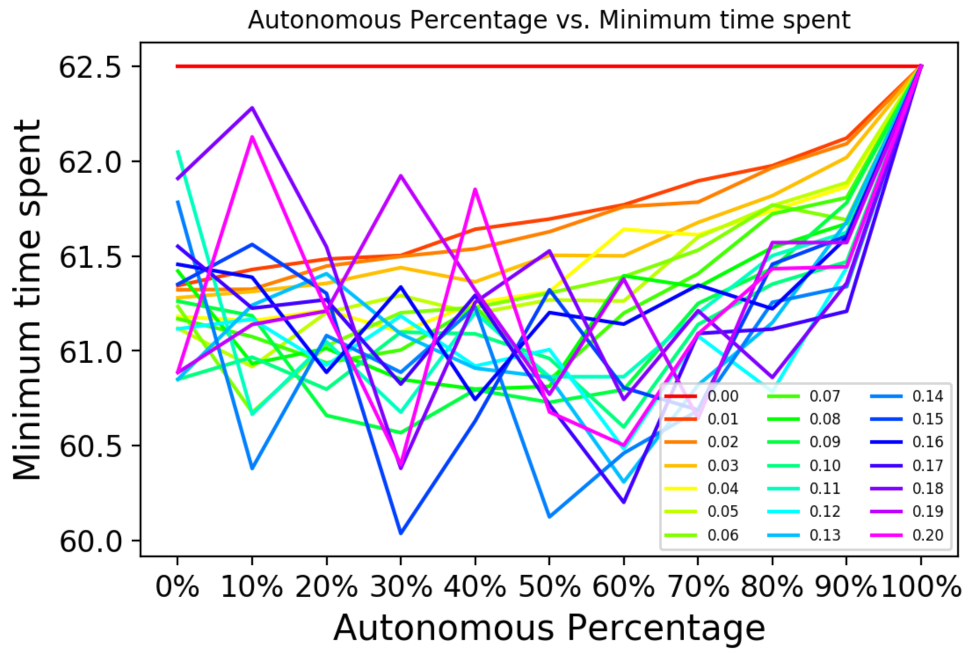


Figure 4.5

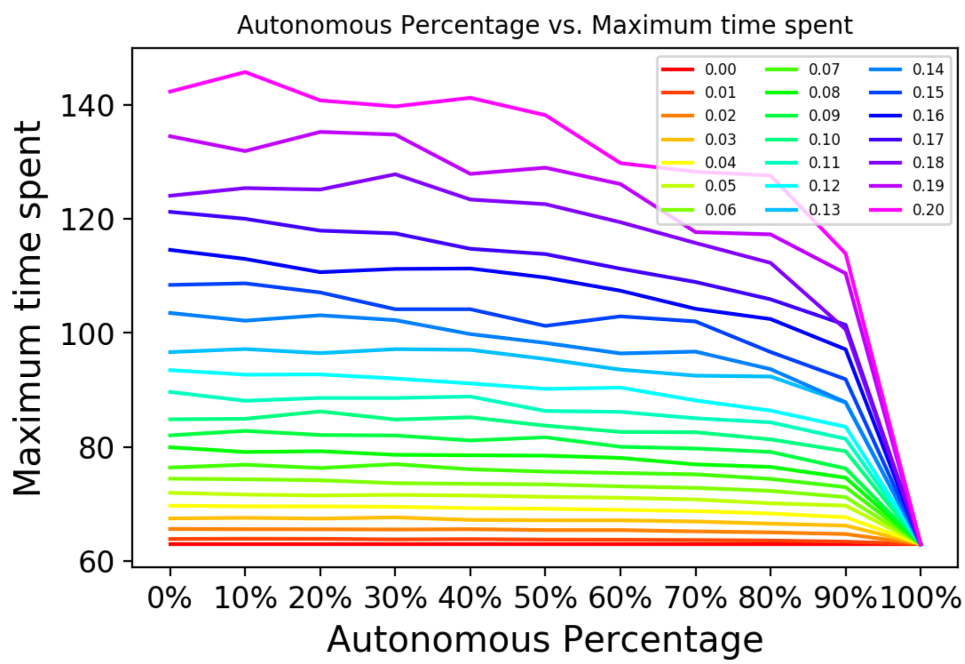


Figure 4.6

4.2 Double lane traffic with fast lane

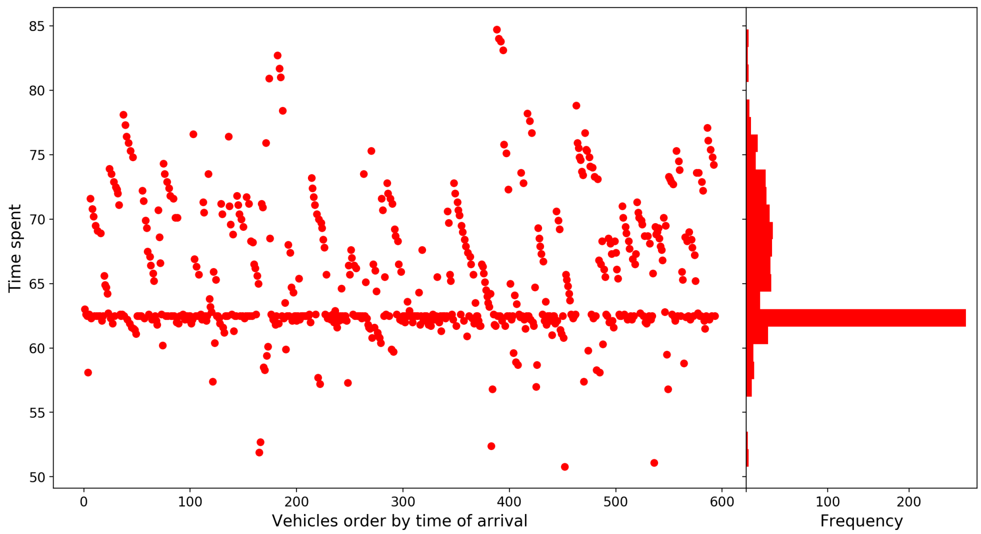


Figure 4.7: Double lane with fast lane simulation

Figure 4.14 showed the time taken for vehicles to finish the travel under 10% of $SDMB$ and 50% of AVs, ordered by time of arrival. A significant amount of vehicles finished the trip around 63 seconds, while most other vehicles spent more. The graph implied that those centered around 63 seconds came from those assigned to the fast lane, while vehicles that took longer came from those assigned to the slow lane. A brief analysis found out that vehicles from the fast lane accounted for more than half of the throughput, with its percentage positively correlated to $SDMB$.

The simulation had the same combinations as equation 4.1. The following results were obtained:

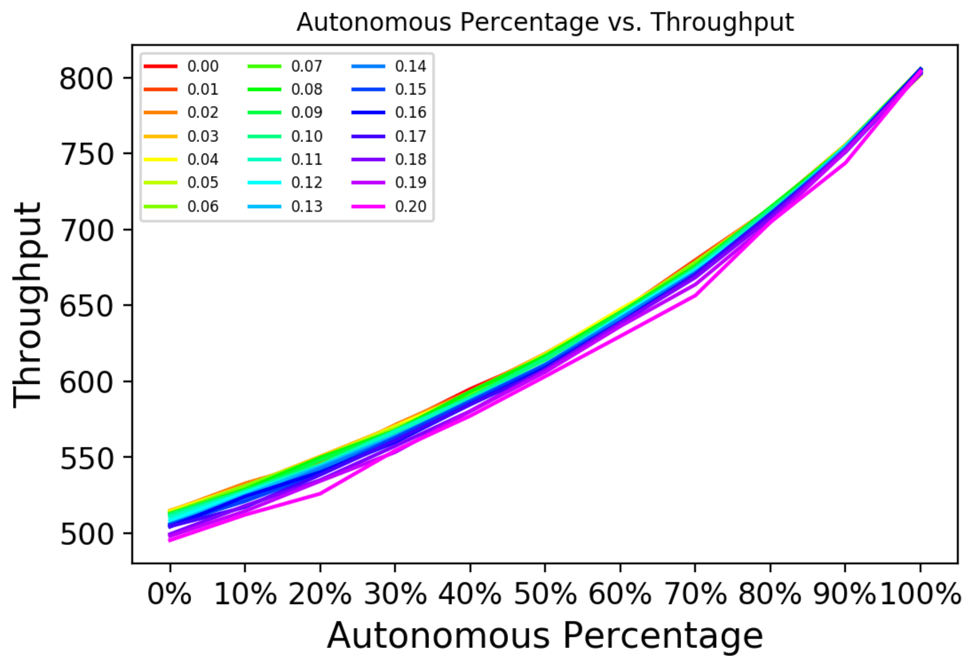


Figure 4.8

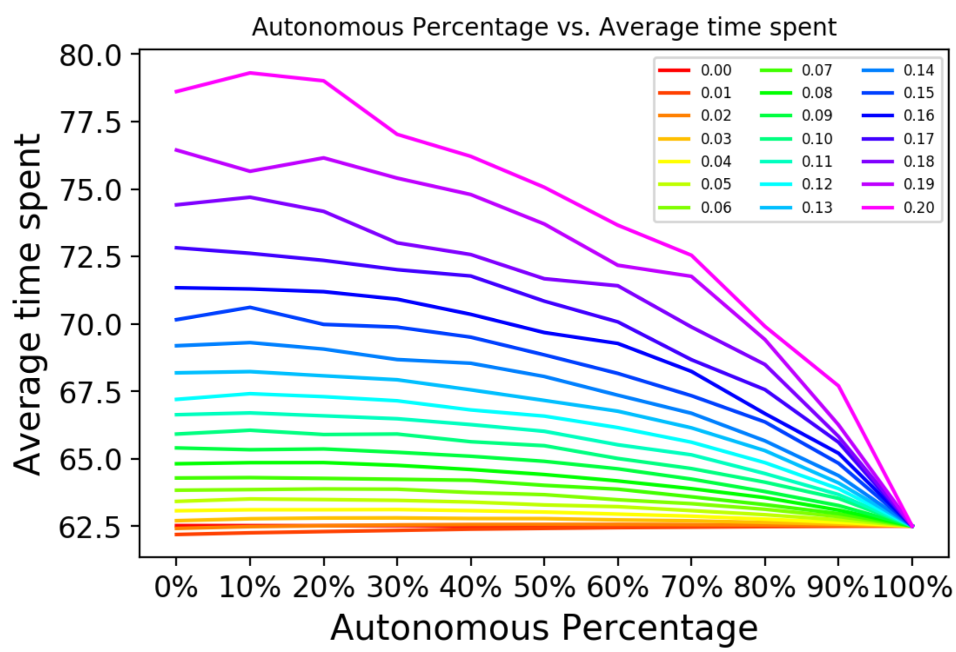


Figure 4.9

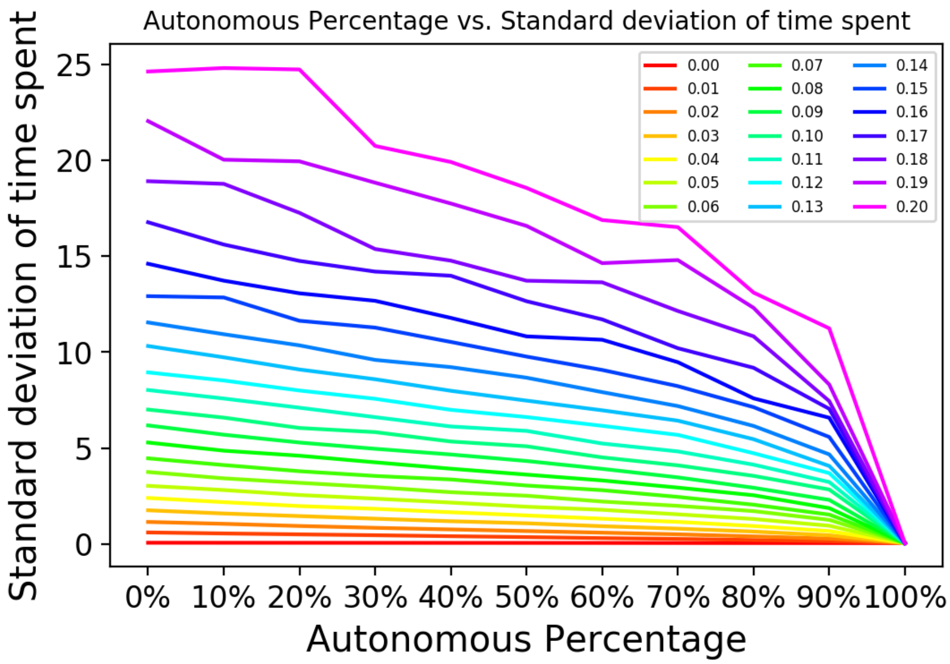


Figure 4.10

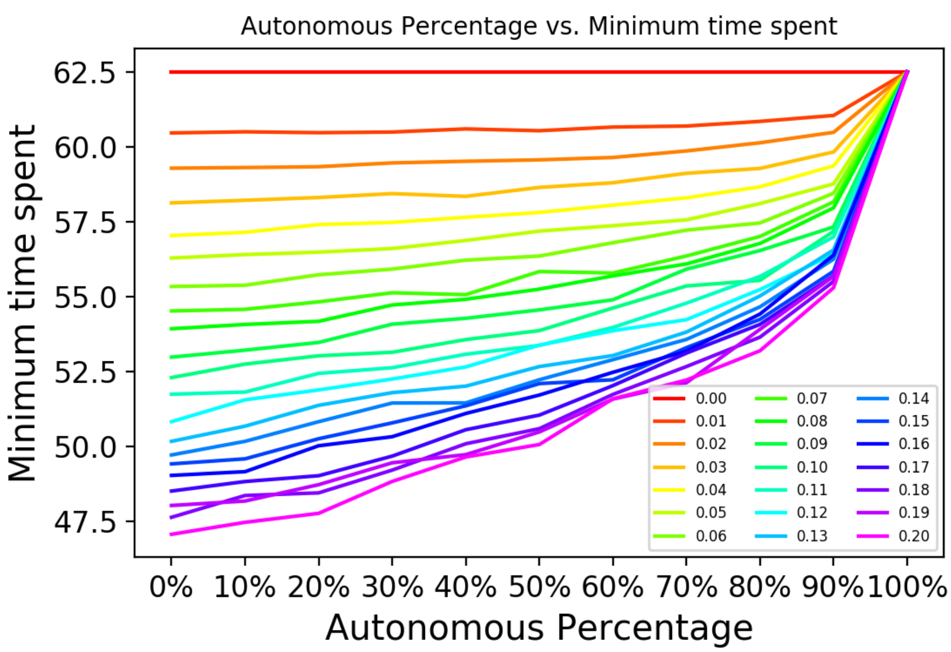
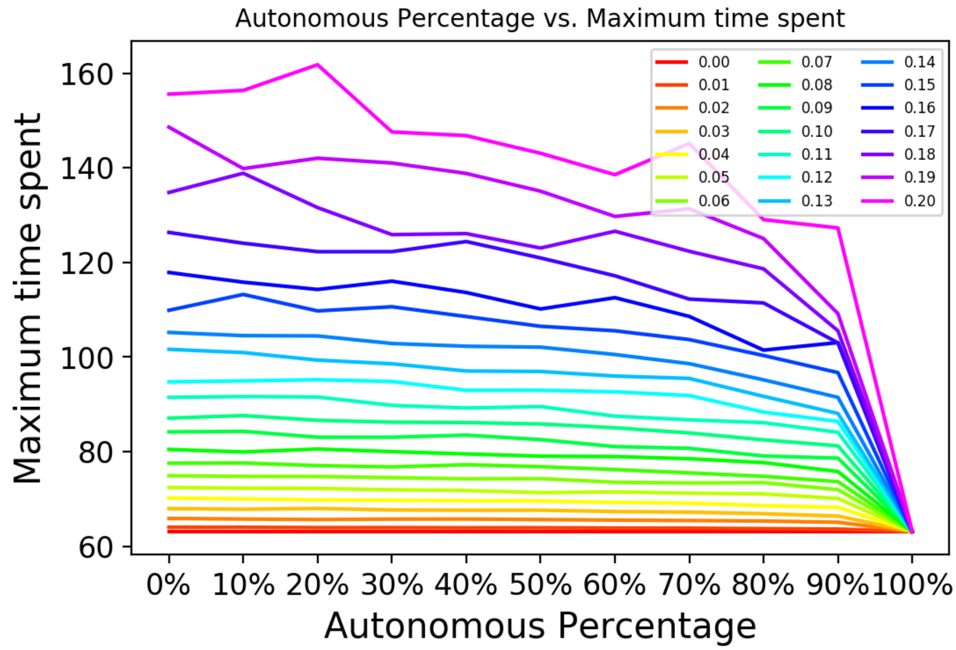


Figure 4.11



Autonomous Percentage vs. Maximum time spent
Maximum time spent
Autonomous Percentage
160
140
120
100
80
60
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
0.14
0.15
0.16
0.17
0.18
0.19
0.20

Figure 4.12

4.3 Double lane traffic with passing lane

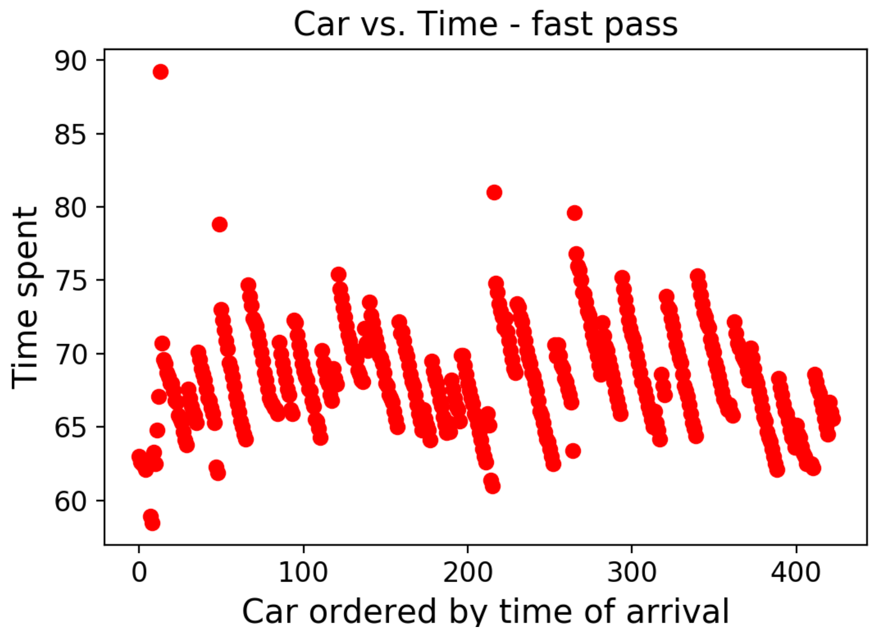


Figure 4.13: Double lane with overtaking lane simulation

Figure 4.7 showed the time taken for vehicles to finish the travel under 10% of $SDMB$ and 50% of AVs, ordered by time of arrival. A similar pattern where the travel time of every vehicle was influenced by its preceding vehicle could still be observed. A major difference was that a small number of observations were found disconnected from the general pattern. A possible explanation was that vehicles with higher comfortable speed would overtake its preceding vehicles instead of driving at a low speed. Notice that the overtake would only happen when all conditions were satisfied, which implied that a vehicle must have a relatively high comfortable speed compared to the average to facilitate an overtake. On the other hand, vehicles with lower speed would still drive at a low speed, which explained the disconnected observations over 75 seconds.

The simulation had the same combinations as equation 4.1, with an addition statistics *takeover*, which recorded the average number of overtakes throughout the simulation. The following results were obtained:

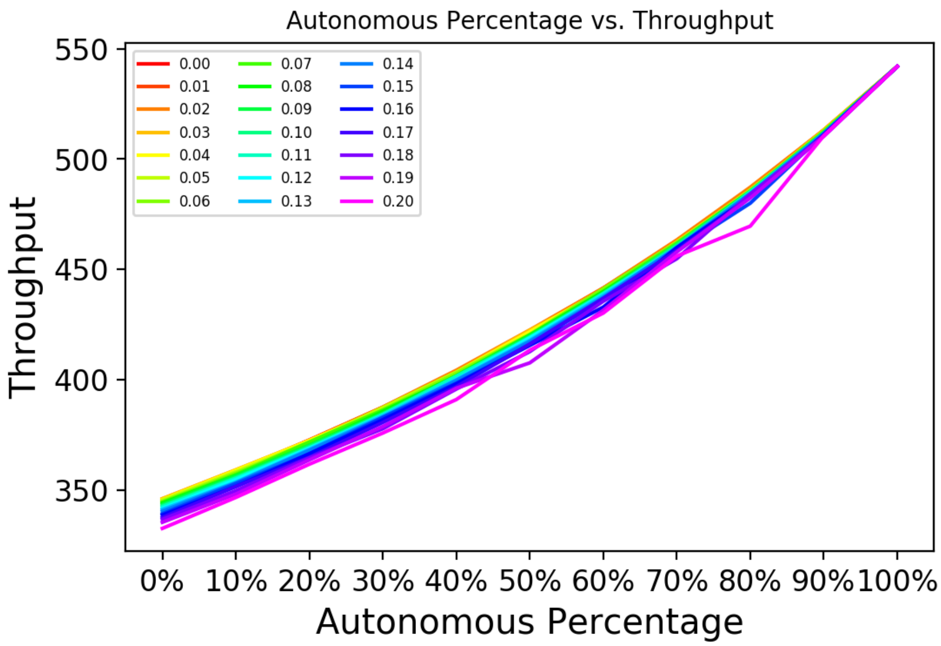


Figure 4.14

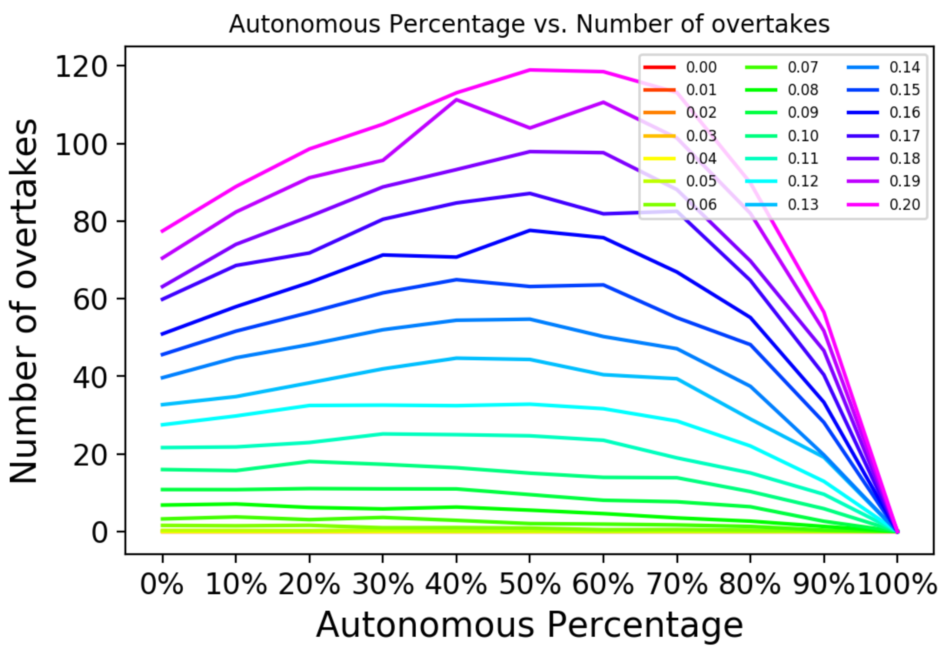


Figure 4.15

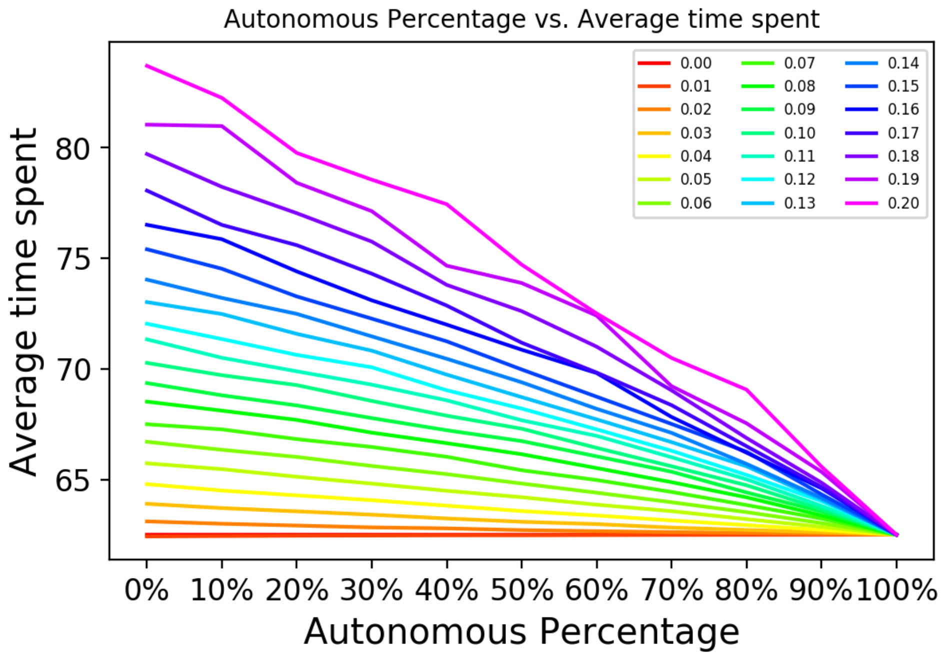


Figure 4.16

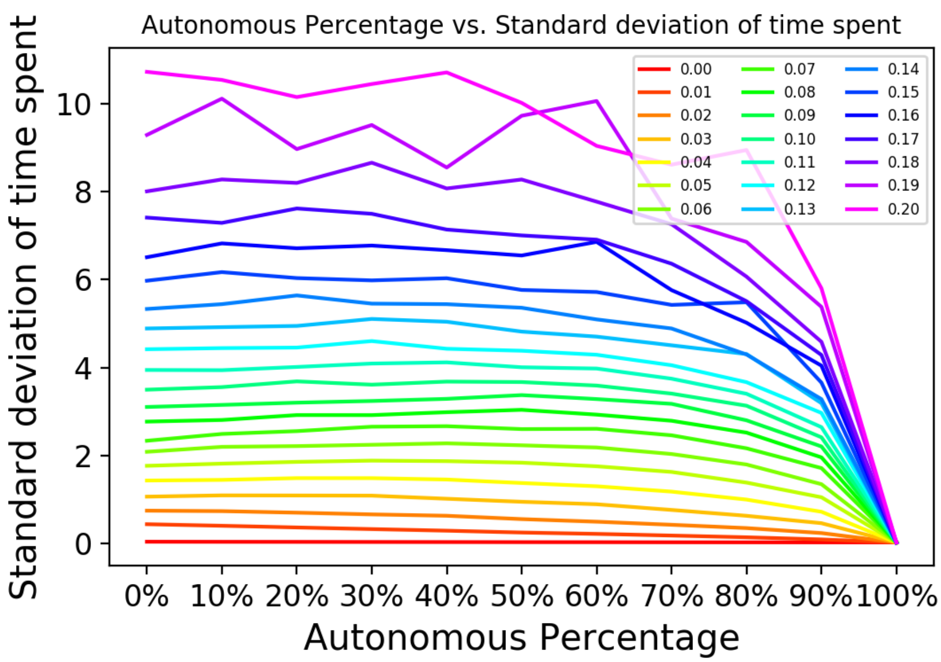


Figure 4.17

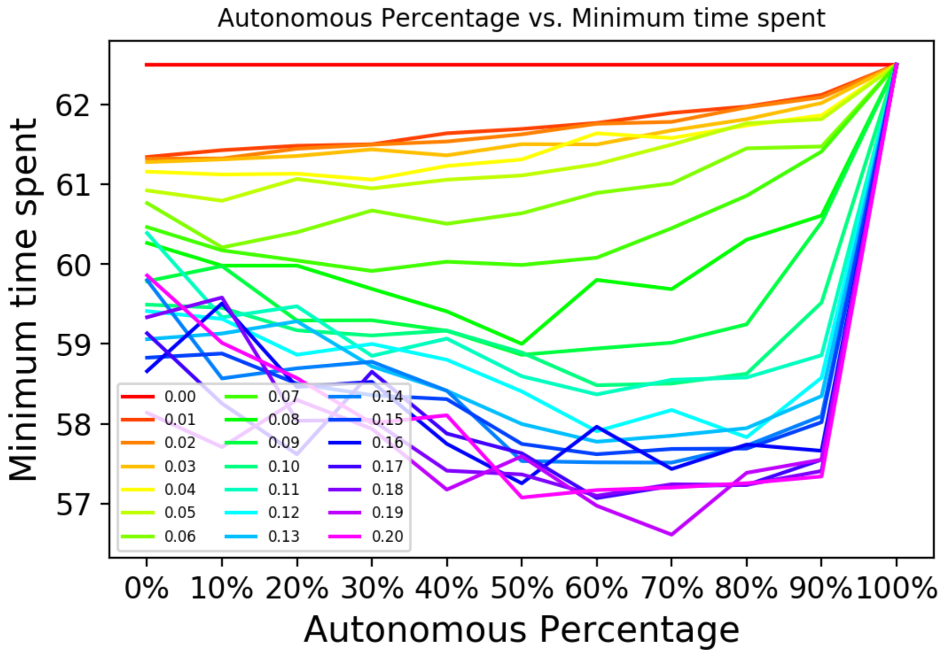


Figure 4.18

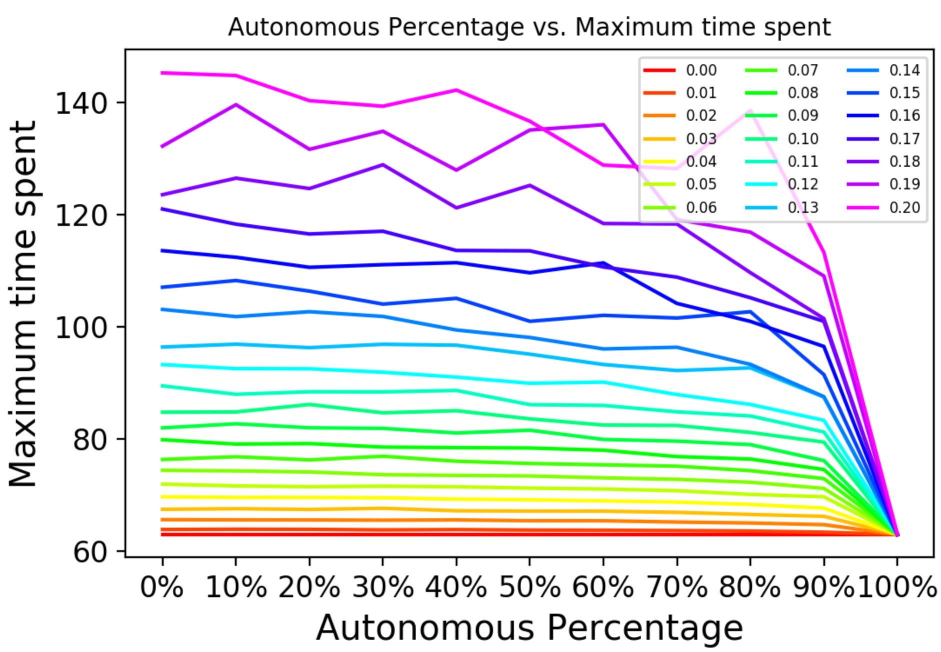


Figure 4.19

4.4 Intersection

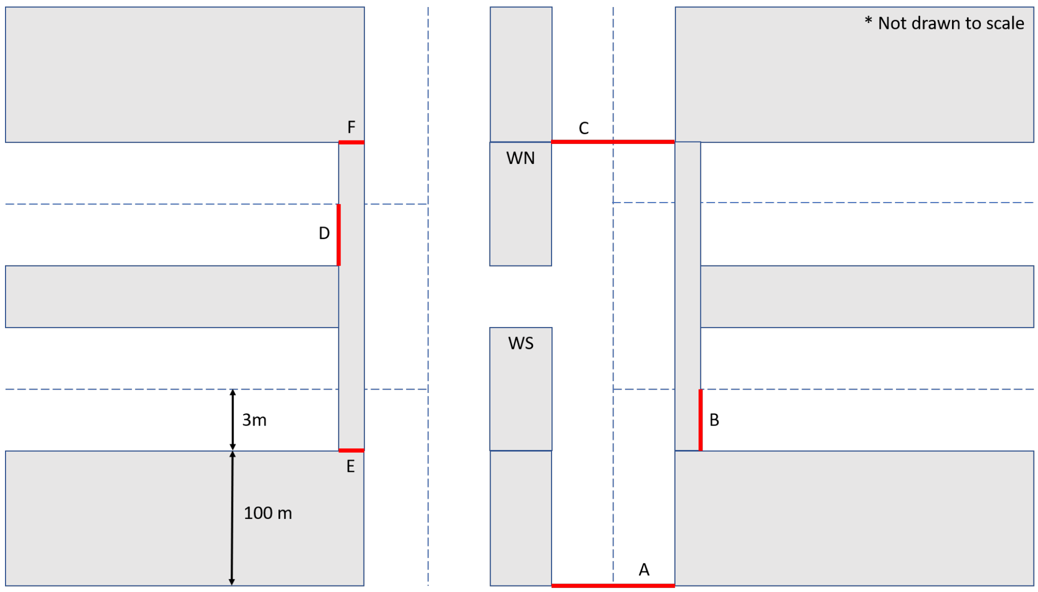
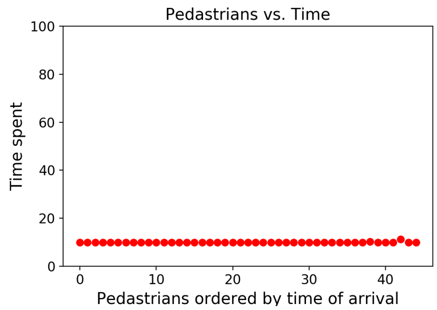


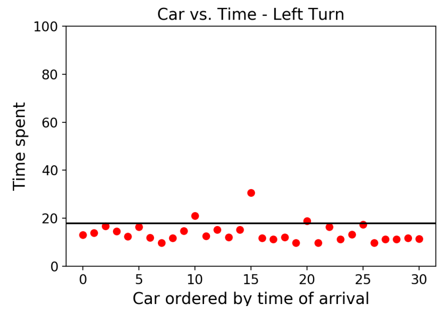
Figure 4.20: Intersection map

The map of the interaction simulation was shown in figure 4.4. The travel time for each type of agent was defined as followed:

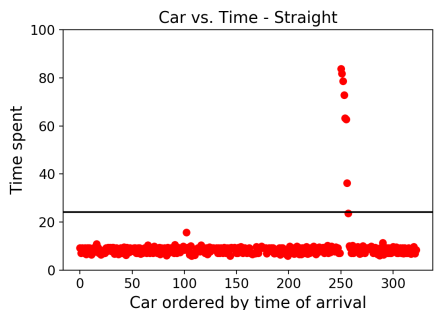
- Straight lane vehicles: duration between the front of the vehicle passing line A, and the front of the vehicle reaching line C.
- Left turn vehicles: duration between the front of the vehicle passing line A, and the back of the vehicle passing line D.
- Right turn vehicles: duration between the front of the vehicle passing line A, and the back of the vehicle passing line B.
- Pedestrians: duration of the pedestrian traveling from line E to F.



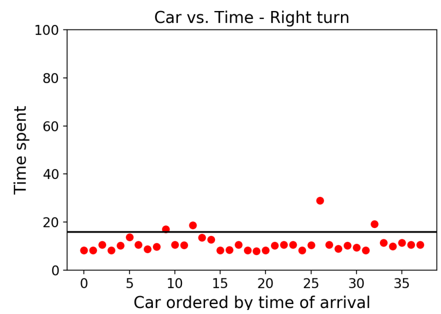
(a) Pedestrians



(b) Left turn vehicles



(c) Straight vehicles



(d) Right turn vehicles

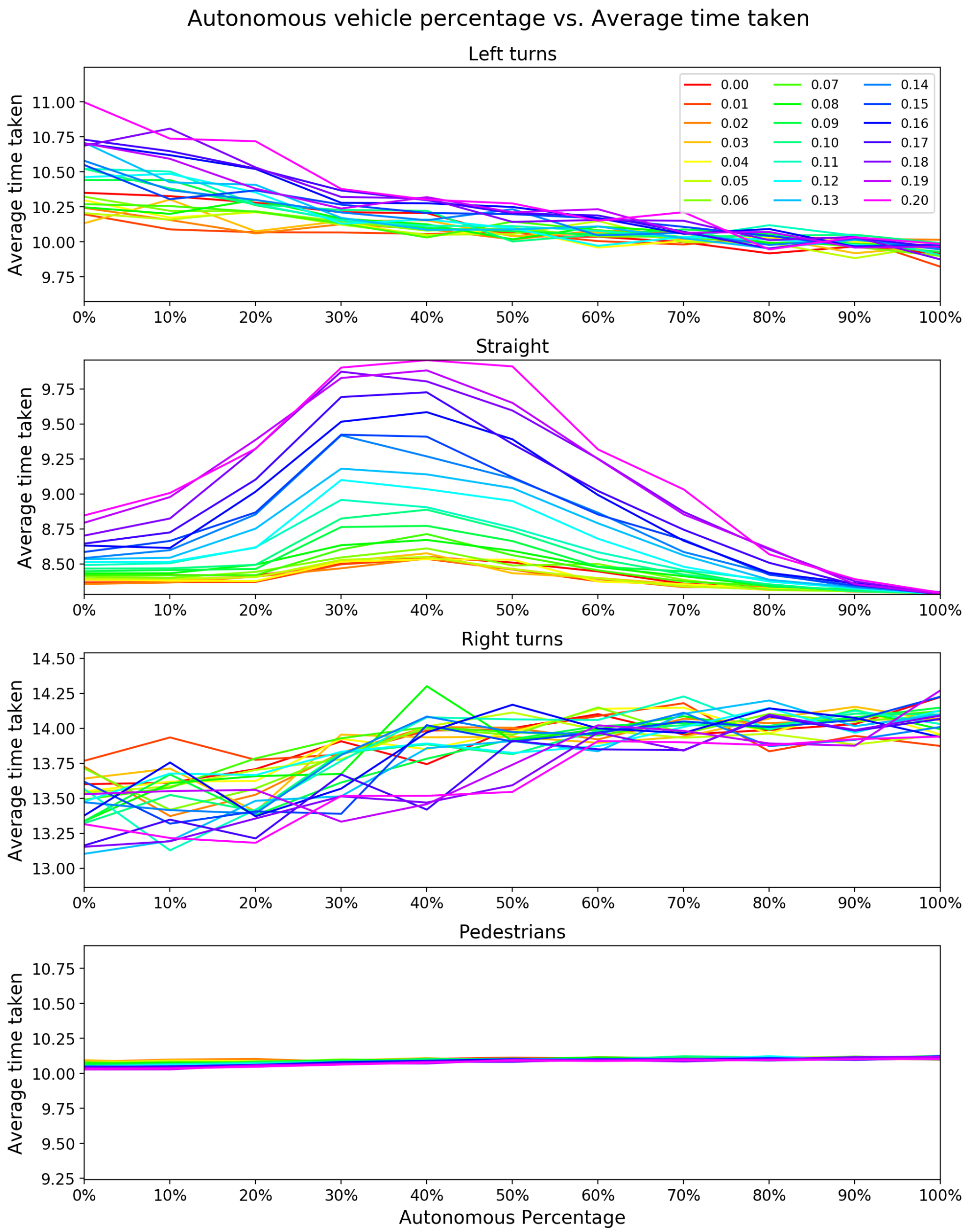
Figure 4.21: Time taken ordered by time of arrival, with vertical lines indicating outliers

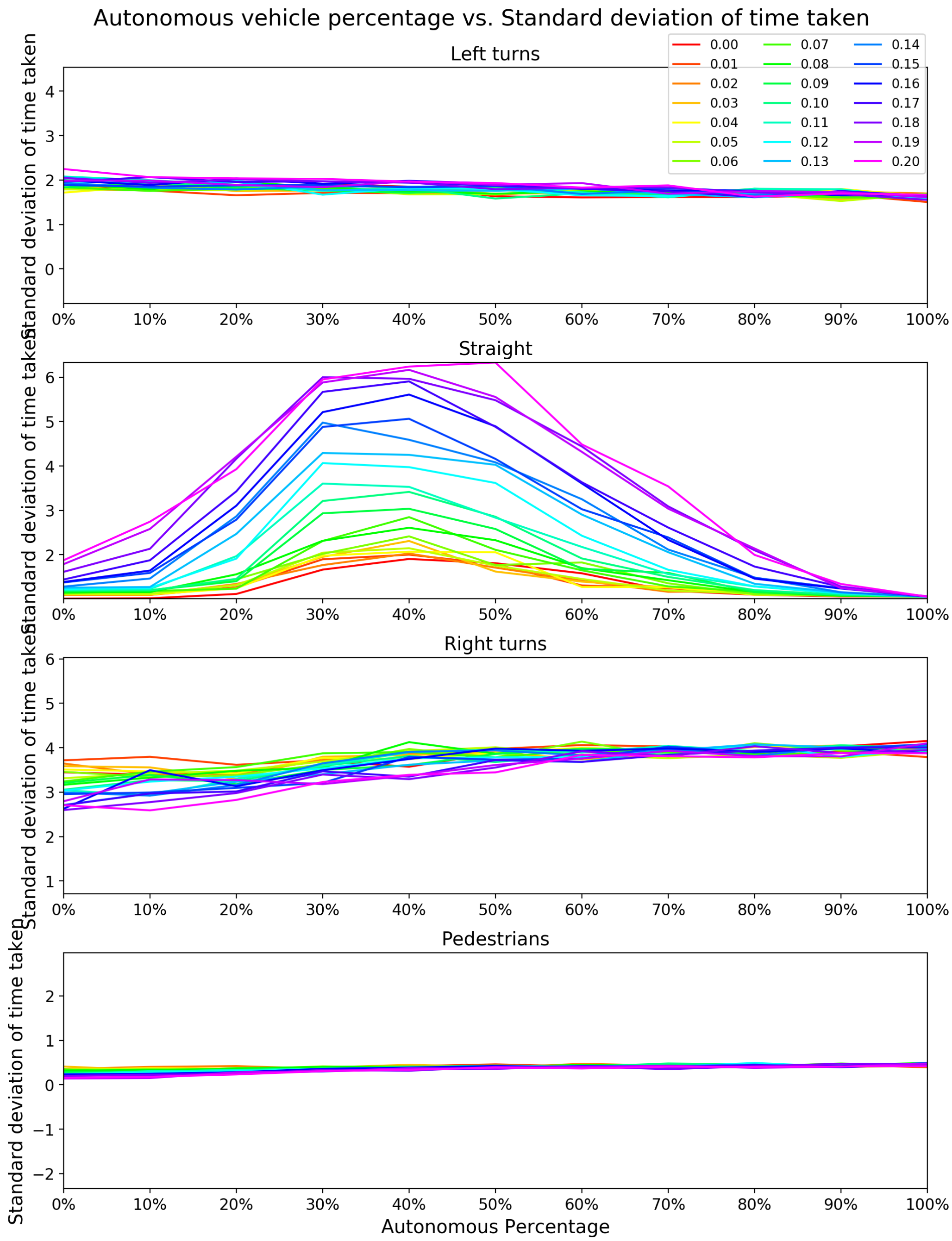
Figure 4.21 showed the time taken for each type of travel agent under 10% of $SDMB$ and 50% of AVs. The vertical axes were normalized such that the four graphs share the same time range. As shown above, the range for straight vehicles was exaggerated due to a small percentage of outliers. While the summary of the results should not be distorted by these outliers, its presence should still be recognized. Therefore, results for vehicles were pre-processed, and the number of outliers removed was recorded. In each type of agent, a timing would be considered an outlier if it satisfied one of the following conditions:

- Two or more standard deviations above the average time of the list
- Two or more standard deviations below the average time of the list, but rarely happened due to the distribution of the results
- More than 60 seconds

In figure 4.21, two horizontal lines were drawn to indicate the upper and lower thresholds for outliers. Note that the three sub-figures only included one horizontal line. This was because the lower thresholds for outliers were all below 0 second.

The simulation had the same combinations as equation 4.1, while the statistics were recorded individually for each type of traffic agent. The percentage of outliers were also recorded, and the following results were obtained. Note that the vertical axis of each sub-figure in the same figure was normalized such that they share the same time ranges.


Autonomous vehicle percentage vs. Average time taken
Left turns
Straight
Right turns
Pedestrians
Average time taken
Autonomous Percentage
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09 0.10 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.20
Figure 4.22



Autonomous vehicle percentage vs. Standard deviation of time taken
Left turns
Straight
Right turns
Pedestrians
Standard deviation of time taken
Autonomous Percentage
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09 0.10 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.20

Figure 4.23

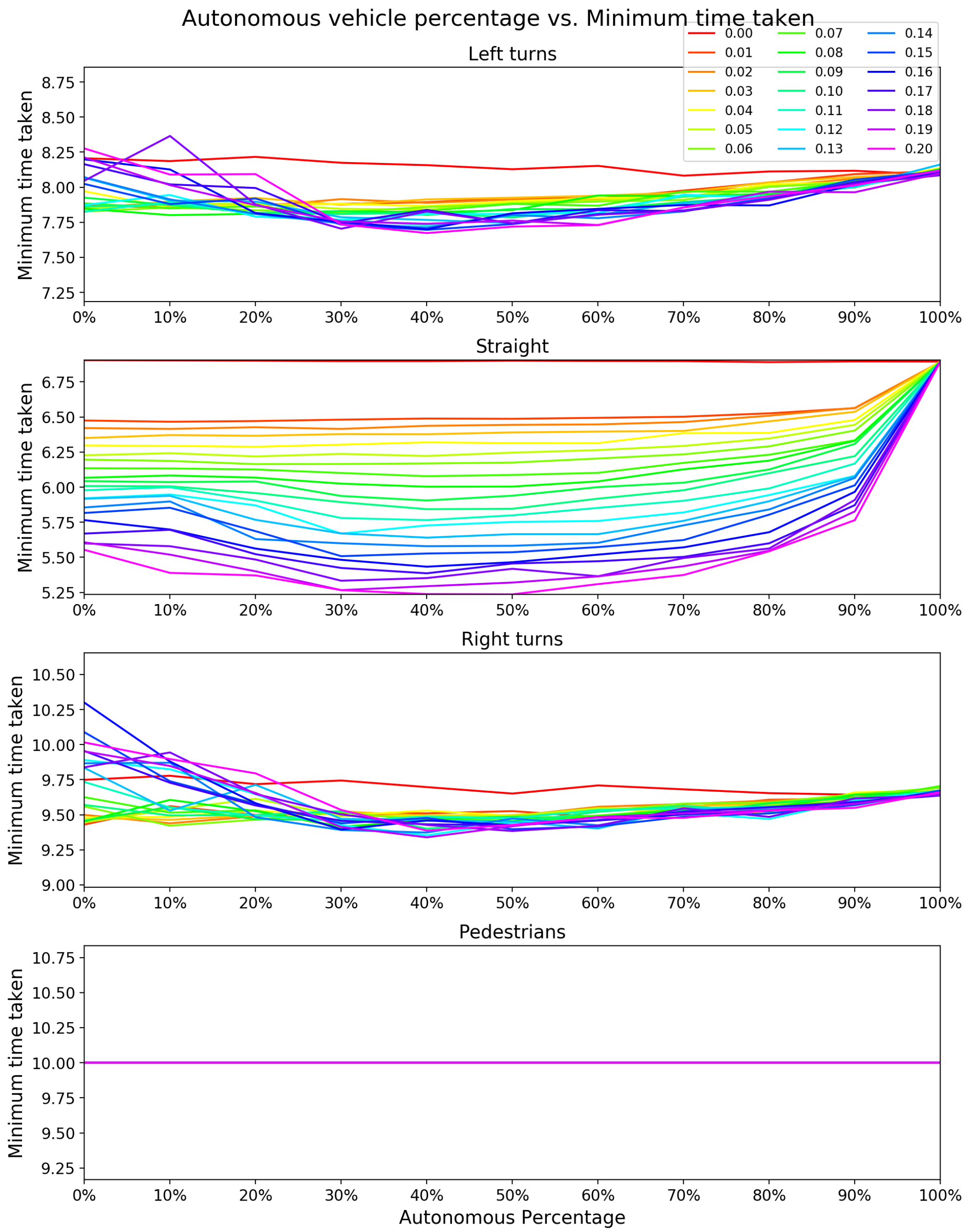
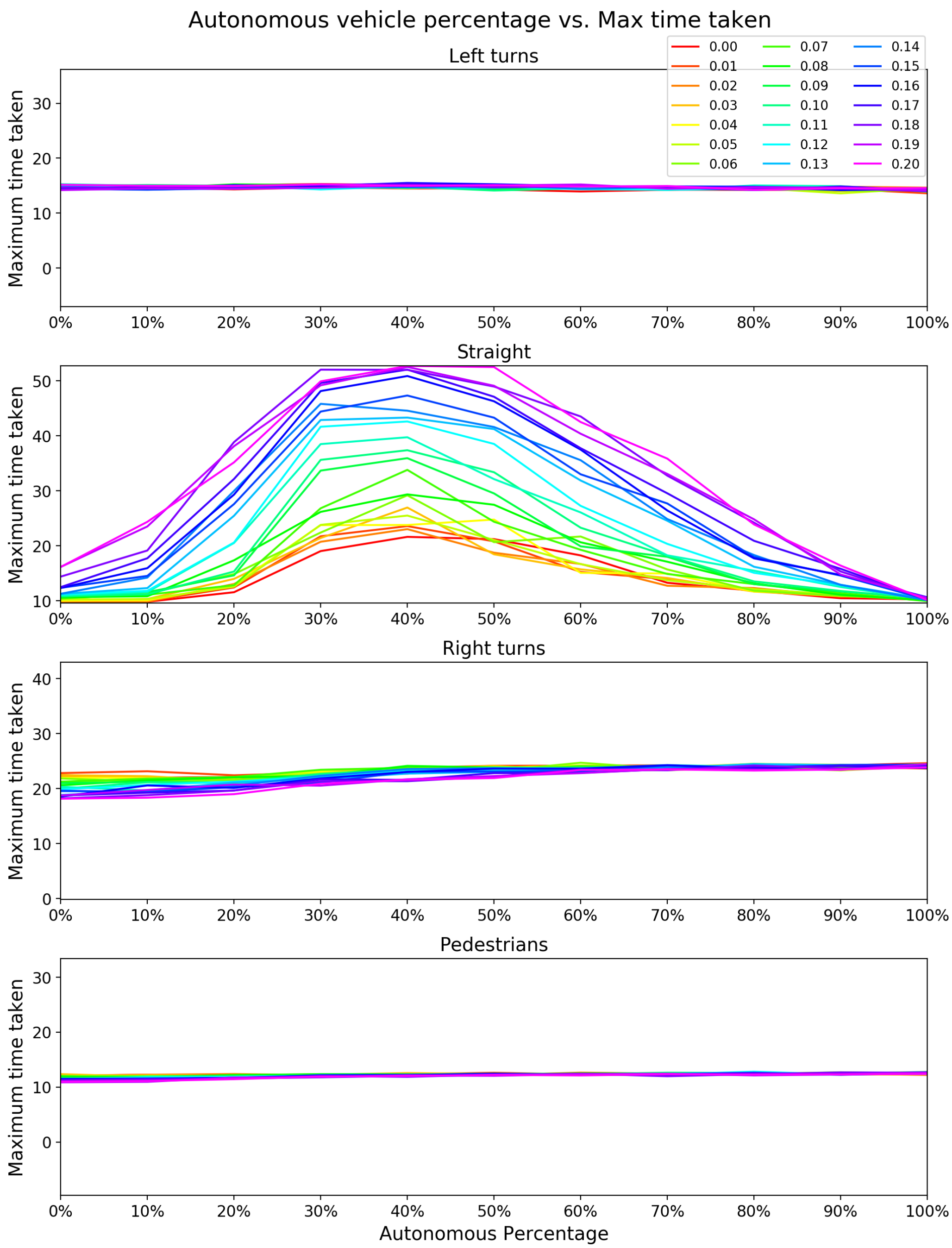

Autonomous vehicle percentage vs. Minimum time taken
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
0.14
0.15
0.16
0.17
0.18
0.19
0.20
Left turns
Straight
Right turns
Pedestrians
Minimum time taken
Autonomous Percentage
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

Figure 4.24


Autonomous vehicle percentage vs. Max time taken
Left turns
Straight
Right turns
Pedestrians
Maximum time taken
Autonomous Percentage
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
0.14
0.15
0.16
0.17
0.18
0.19
0.20
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Figure 4.25

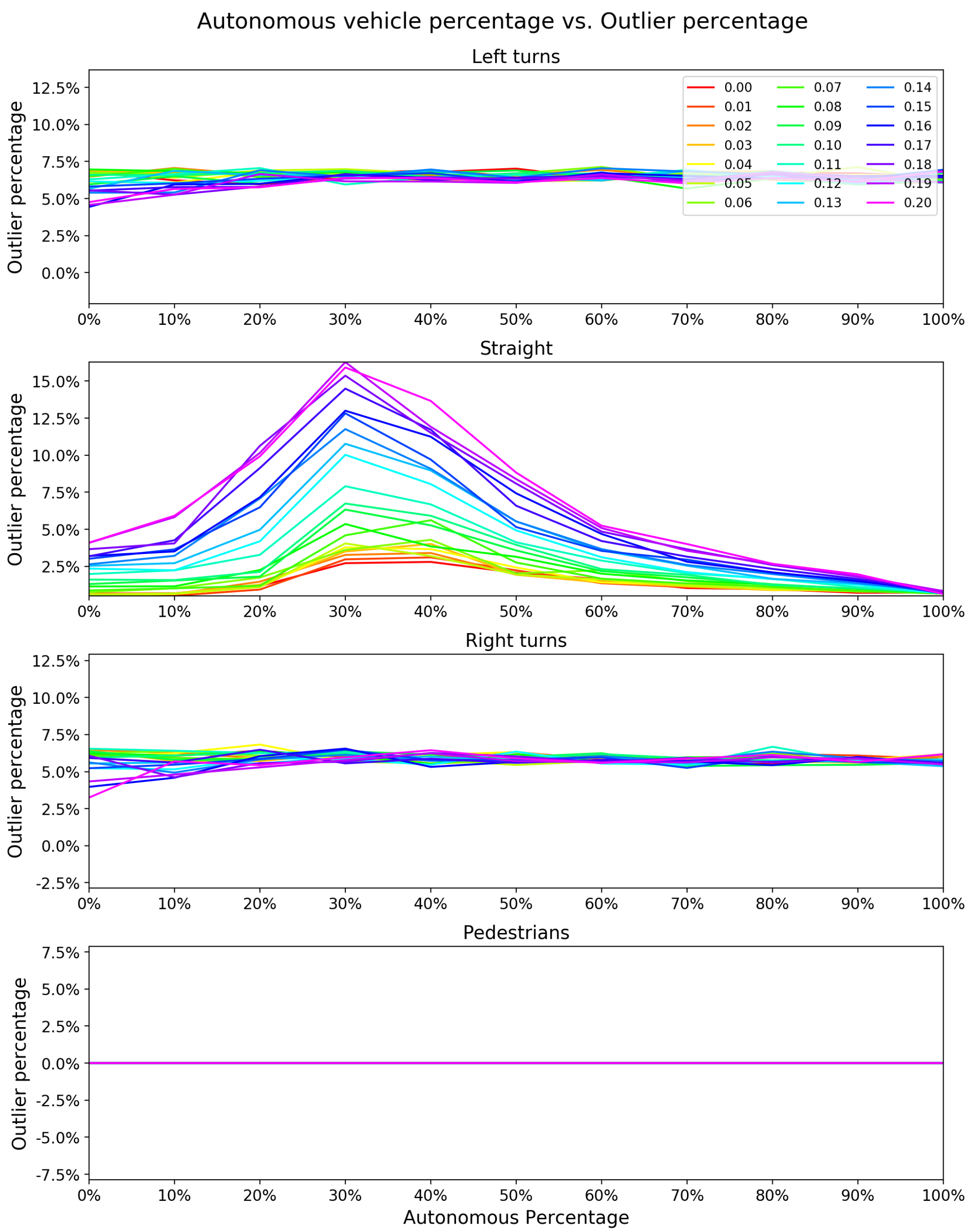

Autonomous vehicle percentage vs. Outlier percentage
Left turns
Straight
Right turns
Pedestrians
Outlier percentage
Autonomous Percentage
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
0.14
0.15
0.16
0.17
0.18
0.19
0.20

Figure 4.26

Chapter 5

Discussion

There were multiple methods to evaluate the *efficiency* of traffic. For example, one could argue that it should be measured by the number of vehicles passed through within a fixed time interval, and road usage was considered optimal when it maximized throughput. Others could emphasize on lowering the standard deviation of time travel to ensure fairness among each traffic agent. As a result, throughput, average time, standard deviation, maximum, minimum of time spent were all recorded to cover different aspects of traffic efficiency.

5.1 Single lane traffic

Figure 4.1 revealed a major downside of single lanes. Without any type of overtaking, the travelling time of each vehicle heavily depended on the speed of its preceding vehicle. When a vehicle had a higher speed than its preceding vehicle, it could do nothing but to wait until it became the leading vehicle of the queue. A vehicle with a significantly low speed could potentially impact multiple vehicles. On the other hand, single lanes require the least cost and land, and could be widely seen in less busy traffic, because the huge gap between each vehicle could mitigate the disadvantage of single lanes.

The increasing percentage of AVs would decrease the variation of driving behaviors, and therefore reduce the frequency of a vehicle with significantly low (or high) speed. Figures 4.2 to 4.4 implied that throughput positively correlated with AV percentage. An increasing AV percentage enabled people to travel more efficiently with lower variation. Note that a zero $SDMB$ was equivalent to 100% of AVs, which explained the horizontal line when $SDMB = 0.00$. Figure 4.5 showed that when AV percentage increased, the frequency of observing vehicles with faster speed would increase. However, when $SDMB$ reached over 0.15, the minimum time spent slightly bounced back, because despite observing even faster vehicles, the high $SDMB$ also led to a higher frequency of vehicles with exceptionally low speed. The low speed of a vehicle would jeopardize its following vehicles, and the impact could propagated even further. Figure 4.6 showed that the maximum time spent was dominated by $SDMB$. This result was was expected because when $SDMB$ was high, vehicles with significantly low speed could still exist even when AV percentage was high.

The downside of single lanes could be improved by adding another lane, either for faster vehicles to overtake slower ones, or for faster lanes to travel at a higher speed. Unsurprisingly, some of the trends above could also be observed in the following simulations.

5.2 Double lane traffic with fast lane

Vehicles were assigned to their designated queue based on their comfortable speed prior to entering the queue. Comfortable speeds of all fast lane vehicles were at least the average speed, and at most the average speed for all slow lane vehicles. Even though it was still possible for a vehicle to be blocked by its preceding vehicle, the assignment reduced the speed difference: when a fast vehicle was blocked by its preceding vehicle, it could still travel at average speed or above; when a slow lane vehicle blocked its following vehicles, the comfortable speed of the impacted vehicles were at most the average speed.

Figure 4.7 revealed that roughly half of the vehicles constantly finished the travel between 61 and 64 seconds. Most of these observations were vehicles travelling in the fast lane. The observations above 65 seconds also showed similar patterns as the single lane simulation with the same reason. A exceptionally slow vehicle in the slow lane forced its following vehicles to travel at a slower speed.

Figures 4.8 to 4.12 followed similar patterns as those of the single lane simulation, except for their scale. Throughput increased by about 60%, primarily because the second lane allowed more traffic. Average time was reduced, especially when AV percentage was low. Standard of deviation of travel time increased because faster vehicles were allowed to travel faster even if blocked, and minimum time also decreased as a result. Note that the time did not bounce back at high $SDMB$ because fast vehicles had more freedom to travel at a more desired speed. Maximum time remained nearly the same because the slowest vehicles would still travel at their own comfortable speed.

5.3 Double lane traffic with overtaking lane

With a overtaking lane, faster vehicles were allowed to overtake a slower vehicle if all the conditions were satisfied. Recall that a vehicle would be allowed to initiate an overtake if and only if:

1. its comfortable speed was significantly higher than that of its preceding vehicle

2. and there was sufficient space in front to fit an overtake

This explained figure 4.15, in which a higher $SDMB$ increased the frequency of sufficing the conditions, and therefore increased the number of overtakes. An interesting result was that at high $SDMB$, the number of overtakes peaked at around 60% of AVs. The characteristics of AVs impacted the number of overtakes in two ways:

1. AVs had no variance in comfortable speed. When AV percentage increased, the variance of vehicle comfortable speed decreased, which made the first condition harder to be satisfied.

2. AVs required shorter safety distance. When AV percentage increased, the second condition was easier to be satisfied.

Therefore, the increase of AVs percentage had mixed impacts on the number of overtakes. The second characteristic of AVs dominated when AV percentage was below 60%, and the first characteristic dominated when AV percentage was above 60%.

The average, standard deviation, minimum and maximum time taken shared similar patterns with those of the previous two simulations.

5.4 Intersection

Time axes for figures 4.22 to 4.26 were normalized such that the four subfigures shared the same range. Vehicles that went straight showed the largest variance among the four traffic agents in all statistics. As AV percentage increased, average time taken for left-turn vehicles decreased, while it increased for right-turn vehicles. Vehicles that went straight had the highest average travel time around 40%, which could be explained by the compound effect of a decreasing average travel time for left-turn vehicles, and an increasing average travel time for right-turn vehicles.

$SDMB$ also played an important role in average travel time, and impacted different traffic agents in various ways. For left-turn vehicles, as $SDMB$ increased, the average time first decreased, then increased. It could be explained by considering how an increasing $SDMB$ could have positive and negative impacts on the average time. As manual drivers had a higher variance in driving behavior, faster vehicles could be blocked by slower vehicles as overtakes were not allowed in this simulation. On the other hand, when a slow vehicle blocked its following vehicles, it created a gap before itself, which enabled more opportunities for turns from the other side. Therefore, the first effect dominated at high $SDMB$, and the second effect dominated at low $SDMB$.

$SDMB$ affected average time taken for right-turn vehicles little. Recall that right-turn vehicles only had to consider the pedestrian lane on the same side to initiate a turn. Due to the low frequency of pedestrians, right-turn vehicles rarely accumulated, and therefore had little effect on the average time. Average time for vehicles that went straight was positively related to an increasing $SDMB$ for the same reasons in the single lane simulation, and the effects were exacerbated by the fact that they were occasionally blocked by left-turn vehicles.

For similar reasons, waitings on left-turn vehicles happened more frequently when AV percentage was around 40%, which explained a higher standard deviation of time spent and outlier percentage. Minimum time, outlier percentage shared similar characteristics as those in the single lane simulation. Due to pre-processing of data, the upper limit for roughly followed the average time spent with an increasing offset around 40%. While it effectively removed outliers, it also made the *maximum* statistics less meaningful.

Chapter 6

Conclusion

The paper explores how a variable standard deviation of manual driving behavior and AV percentage can impact the current traffic. While results show that a higher AV percentage does not necessary lead to a more efficient outcome in every case, it does show promising results for the future development of AVs. Compared to full manual driving vehicles at $SDMB = 0.20$, full AV increases throughput by nearly 60% in single and double lane simulations, and the average time taken was reduced by roughly 30%. On the other hand, the results also raise other concerns. When AV percentage is below 40%, an increase in AV percentage leads to a more chaotic double lane traffic with overtaking lane, as the number of overtakes increases. A majority of vehicles also suffer from a longer time to travel in the interaction simulation. As a result, it may be challenging for AVs to gain social acceptance, as people initially experience the downsides of the new technology.

Human behaviors are extremely hard to predict, and humans certainly do not behave under the assumptions made in these simulations. People rarely strictly abide by traffic rules, and they usually make reasonable modifications to travel more efficiently while maintaining high level of safety. For example, manual drivers are inclined to drive above speed limit on a sunny day with little traffic. On the other hand, an increase of AV percentage makes traffic easier to predict due to their low variance. While AVs have the potential to eliminate most of the traffic accidents by strictly following traffic rules, they lack the flexibility of making *smart* moves.

The simulation results show that average travel time can be significantly reduced with a decrease of $SDMB$. Compared to manual drivers, AVs can be considered as traffic agents with little to no variation, and is therefore easier to predict. Traffic inefficiencies, such as a slow vehicle blocking following vehicles, can be reduced if vehicles have more uniformed behaviors. AVs also require shorter safety distance, which can significantly raise the throughput by enabling more vehicles to travel at once. Nonetheless, AV developers should also consider its side effects, such as whether manual drivers can feel uncomfortable when its following vehicle gets too close, and pressure to drive faster.

A logical follow-on to this paper is to predict human response to an increasing percentage of AVs on the road. We believe, with substantial reasons, that when AVs are first introduced to the market, people are skeptical and hesitant to try the new product. Other traffic agents will not take advantage of its conservative algorithms, and can behave even more cautiously because it takes time for AVs to establish trust within the society. However as AV techniques mature, some manual drivers start making selfish decisions, and still get to their destinations safely at the expense of traffic efficiency. This will incentives more people to behave more selfishly, and eventually lead to an inefficient outcome. Therefore, researchers have to constantly modify their algorithms to adapt to the changing behavior.

References

1. Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B, Coughlin, J. (2016). Autonomous vehicles and alternative to driving: trust, preferences, and effects of age. https://agelab.mit.edu/system/files/2018-12/2017_TRB_Abraham.pdf. Accessed Nov 17, 2019.

2. Esposito, M. (2019). Perspective - The Future of Government: Navigating Legislation in the Sharing Economy. *Future Governments*. https://www.emerald.com/insight/content/doi/10.1108/S2048-757620190000007018/full/html. Accessed Dec 31, 2019.

3. Fisac, J., Bronstein, E., Stefansson, E., Sadigh, D. Sastry, S. Dragan, A. (2018). Hierarchical game-theoretic planning for autonomous vehicles. https://arxiv.org/pdf/1810.05766.pdf. Accessed Nov 17, 2019.

4. Henschke, A. (2019). Trust and resilient autonomous driving systems. *Ethics and Information Technology*. https://link.springer.com/content/pdf/10.1007/s10676-019-09517-y.pdf. Accessed Dec 31, 2019.

5. Hevelke, A. Nida-Rümelin, J. (2014). Responsibility for Crashes of Autonomous Vehicles: An Ethical Analysis. *Science and Engineering Ethics*. https://link.springer.com/content/pdf/10.1007%2Fs11948-014-9565-5.pdf. Accessed Dec 31, 2019.

6. McAllister, R., Gal, Y., Kendall, A., Wilk, M., Shah, A., Cipolla, R., Weller, A. (2017). Concerte problems for autonomous vehicle safety: advantages of Bayesian deep learning. https://www.repository.cam.ac.uk/bitstream/handle/1810/266683/McAllister.pdf?sequence=5. Accessed Nov 17, 2019.

7. Marchant, G. Lindor, R. (2012). The Coming Collision Between Autonomous Vehicles and the Liability System. *Santa Clara Law Review*. http://digitalcommons.law.scu.edu/cgi/viewcontent.cgi?article=2731&context=lawreview. Accessed Dec 31, 2019.

8. Nielsen, T., Haustein, S. (2018). On sceptics and enthusiasts: What are the expectations towards self-driving cars? *Transport Policy 2018*. https://www.sciencedirect.com/science/article/pii/S0967070X17302937. Accessed Nov 12, 2019.

9. Queesland Government. (2016). Stopping distances: speed and braking. https://www.qld.gov.au/transport/safety/road-safety/driving-safely/stopping-distances. Accessed Dec 19, 2019.

10. Steinke, N., Ulbrich, F., Goehring, D. Rojas, R. (2018). Traffic mapping for autonomous cars. *2018 IEEE Intelligent Vehicles Symposium (IV)*. http://www.mi.fu-berlin.de/inf/groups/ag-ki/publications/Traffic-mapping/steinke18iv-trafficmapping.pdf. Accessed Nov 17, 2019.

11. Tussyadiah, I., Zach, F., Wang, J. (2017). Attitudes toward Autonomous on Demand Mobility System: The Case of Self-Driving Taxi. https://www.tussyadiah.com/ENTER2017-Self-Driving%20Taxi_FINAL-1.pdf. Accessed Nov 22, 2019.

12. Vinkhuyzen, E., Cefkin, M. (2016). Developing socially acceptable autonomous vehicles. *EPIC 2016*. https://anthrosource.onlinelibrary.wiley.com/doi/pdf/10.1111/1559-8918.2016.01108. Accessed Nov 17, 2019.

13. Wickert, G., Matthiesen, Lehrer. (2018). Slower Traffic Keep Right: A Summary of State 'Keep Right' Traffic Laws. *Claims Journal*. https://www.claimsjournal.com/news/national/2018/06/07/285097.htm. Accessed Dec 19, 2019.

14. Wolf, I. (2016). The Interaction Between Humans and Autonomous Agents. *Autonomous Driving*. https://link.springer.com/content/pdf/10.1007%2F978-3-662-48847-8.pdf. Accessed Dec 31, 2019.

15. Yang, J., Coughlin, J. (2014). In-vehicle technology for self-driving cars: advantages and challenges for aging drivers. *International Journal of Automotive Technology, Vol 15, No. 2, pp. 333-340 (2014)* `https://link.springer.com/content/pdf/10.1007/s12239-014-0034-6.pdf`. Accessed Nov 17, 2019.

Appendix

The source code can be found at my GitHub repository: `https://github.com/ericwang1997/CS499`. The repository consists of four folders, which include source code and results for single lane traffic, double lane traffic with overtaking and fast lane, and intersection simulations. In each folder, the *ipynb* file is the jupyter notebook file which includes all the source code for generating the simulation results. Raw data were stored as csv files in the *csv* folder, and their corresponding graph visualizations were stored as png files in the *graphs* folder. Each csv file consists of 21×11 data entries. Each row corresponds to a particular $SDMB$ from 0.00 to 0.20, and each column corresponds to a particular AV percentage from 0% to 100%.