Using Agent-Based Vehicle Traffic Models to Analyze Traffic Flow

By

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfilment of the requirements of the degree of

MASTER OF SCIENCE

Department of Electrical and Computer Engineering

University of Manitoba

Winnipeg

Contents

Abstract

This thesis discusses the creation of an agent-based model for vehicle traffic that uses a previously developed mathematical car-following micro-simulation model. The agent-based model results are verified against the original model. The agent-based model is then used to explore the effects of inclement weather and autonomous drivers on traffic to explore the suitability of using the agent-based approach to model traffic. The primary environment focused on is a signalized four-way intersection, with an extension to freeways for autonomous vehicle simulation. The model is used to demonstrate how optimizing green light intervals at intersections based on current weather conditions can help to partially restore traffic throughput to normal condition levels. Results from simulations with autonomous vehicles demonstrate that traffic flow steadily increases as these vehicles enter the driving population. In the case of signalized intersections this improvement increases in inclement weather, but increases are flat across different weather conditions for freeways. The model is developed to be parametric so that it can be used in the future to study other traffic environment and vehicle behaviors as more information about autonomous vehicles becomes available.

Acknowledgements

I would like to acknowledge the support of my advisor, Dr. Robert McLeod, for introducing me to Agent-Based Modelling and encouraging me to pursue this project for my Master's thesis. I would also like to thank my wife, Sarah, who has supported me through the writing of this thesis.

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Introduction

The flow of vehicles through signalized intersections (hereafter referred to as "intersections") is important to the overall flow of traffic in many cities. The rate at which vehicles move through intersections depends on a variety of factors. Two of the major factors being signal light timing (i.e. how long the light stays green, hereafter referred to as "green interval"), and weather (Goodwin, 2002). Signal light timing affects traffic flow in all areas; how large a role weather plays depends a lot on the time of year and the climate of the geographical region in question. For example, traffic flow can be severely limited by snow and ice but in areas that do not get this type of weather this is not a factor. Another variable that will increasingly become important in the years to come is the introduction of autonomous vehicles into the driving population. The exact behaviour and effect of autonomous vehicles is not yet known, and there are varying opinions in the literature about the level of impact they will have on traffic performance (Metz, 2018; Ye & Yamamoto, 2018). Autonomous vehicles will not only affect intersection traffic, but also major highway/freeway traffic (perhaps to a much larger degree). These issues are just a sample of the many challenges facing transportation engineers. To investigate the causes of traffic problems, and to explore potential solutions to these problems, good modelling and simulation tools are critical. The objective of this thesis was to investigate the use of the Agent-Based Modelling paradigm to develop a method to effectively model vehicle traffic in a way that allowed for the simulation of these different impact factors. The results of the model simulations are analyzed to try and assess if there are strategies or policies to be adopted to help improve traffic flow. In addition, the model was used to simulate the introduction of autonomous drivers into the vehicle population to demonstrate the ability of the model to easily adapt to different types of drivers, and to potentially assess the impact of different driver behaviors

Modelling Methods

Modelling Traffic Flow

Overview of Traffic Models

Many macroscopic models exist for modelling traffic flow on a large scale (Hoogendoorn & Bovy, 2000; Treiber, Hennecke, & Helbing, 1999). Models in this class are based on traditional thermodynamics and treat vehicles somewhat like particles that all obey some fundamental laws. For traffic on a large scale (i.e. – freeway systems) these models can be a good representation of vehicle traffic. These macro level models are less useful when focused down on the level of a single traffic intersection. This is due largely to the fact that vehicles do not move based on fundamental laws of nature, they are currently driven by people with individual driving behaviors. For this type of traffic, a microsimulation model is better suited. Instead of trying to model traffic as a large system, microsimulation models assign behaviours to each unit in the model (the vehicles in this case) and simulate a collection of these units together in a defined environment (traffic intersection or freeway in the case of this project) to see how they interact.

Many microsimulation models for vehicle traffic have been developed over the years, some going back as far as the 1950’s (Chandler, Herman, & Montroll, 1958). This paper will focus on a type of car-following model where the behaviour of each driver is based on what the vehicle in front of them is doing. Several of these models were investigated, the first of which is called the Generalized Force Model (Helbing & Tilch, 1998), and the second is called the Intelligent Driver Model (Treiber, Hennecke, & Helbing, 2000). Both of these models focus on the car following behavior of drivers.

They give a mathematical framework for how the acceleration of each vehicle is calculated over time based primarily on how far away the leading vehicle is, and how fast it is travelling. For this project, these models are treated as Agent-Based Models (ABM). The ABM paradigm gives a set of behaviours to agents and puts them in a system or environment to see what type of collective behaviours arise (Hanappi, 2017). This modelling paradigm is well suited to vehicle traffic since every vehicle can be represented as an agent, and the act of driving is typically governed by a set of rules that most drivers follow (with some variations of course). There are many different environments for vehicle traffic to exist in. For this discussion, the environments have been limited to a single lane four-way intersection, and a stretch of three lane freeway.

Generalized Force Model

The Generalized Force Model (GFM) used the concept of social/generalized forces (referred to hereafter as influences) to describe driver behaviour (Helbing & Tilch, 1998). The model assumes that the primary influences affecting the driver of some vehicle, α, are their target velocity (v^0_α) and their desire to keep a safe distance from other vehicles (β) (Helbing & Tilch, 1998). The desire to reach some target velocity produces a positive acceleration (A^0_α), and the desire to keep a distance between the driver and other vehicles produces a repulsive influence on driver acceleration ($RA_{\alpha,\beta}$). To simplify the repulsive influence, it is assumed that the majority of this influence comes from the vehicle directly in front of the driver (α-1, their leading vehicle), therefor β = α-1. Using these influences, acceleration for a given vehicle can be described using the following equation (Helbing & Tilch, 1998):

$$\frac{dv_\alpha}{dt} = A^0_\alpha(v_\alpha) + RA_{\alpha,\alpha-1}(x_\alpha, v_\alpha; x_{\alpha-1}, v_{\alpha-1}) \quad (1)$$

The parameters v_α and $v_{\alpha-1}$ refer to the velocity of the vehicle in question and of their leading vehicle respectively. The parameters x_α and $x_{\alpha-1}$ refer to the current position on the roadway for the vehicle in question and their leading vehicle respectively. For a more detailed breakdown of the GFM, the reader is encouraged to refer to the original paper. In the first stage of this project, the GFM was selected to describe the driving behavior of vehicle agents in the model. The reason for this was that the vehicle accelerations that arise from the model are reasonably close to real world measurements (they are unrealistically high, but not by a large margin) (Helbing & Tilch, 1998; Jiang, Wu, & Zhu, 2001). Also, there are not a lot of model parameters, and the parameters correspond to real world properties that are easily understood (i.e. acceleration/deceleration time, minimum safe distance).

Intelligent Driver Model

The Intelligent Driver Model (IDM) was developed by Martin Treiber, Ansgar Hennecke and Dirk Helbing (Treiber et al., 2000). It was developed for a variety of reasons, one of which was to improve on the acceleration behaviour of the GFM described above. The GFM has unrealistically small acceleration times which the IDM remedies (Treiber et al., 2000). The IDM has other advantages in describing congested traffic states and other boundary conditions, but the primary motivation for using it in this project was the improved acceleration behaviour since this is one of the primary parameters we adjust to simulate different driving scenarios. The IDM satisfies these four basic conditions for acceleration behaviour (M.~Treiber & A.~Kesting, 2013):

1. Vehicles accelerate smoothly towards a desired velocity (v_0) when there are no other vehicles or obstructions ahead of them, with the acceleration steadily decreasing as the vehicle approaches the target velocity.

2. The acceleration of vehicles is restricted proportionally based on the distance from the leading vehicle. The further away a leading vehicle or obstacle is, the lower the restriction they have on acceleration, reducing to zero when they are outside of some interaction range.
3. The lower the velocity of the leading vehicle, the more the acceleration of a vehicle is restricted. Acceleration decreases at a faster rate the greater the difference between the vehicle and leading vehicle velocity.
4. Vehicles always strive to maintain some minimum gap between them and the leading vehicle or obstacle, but they will not back up if this limit is violated.

In addition to these acceleration behaviours, the model has the following properties (M.~Treiber & A.~Kesting, 2013):

1. The target bumper to bumper distance from the leading vehicle is not less than a safe distance, $s_0 + vT$ where s_0 is the minimum gap discussed above, and T is the desired time gap between the leading vehicle or obstacle. This formula causes the target bumper to bumper distance to increase as the current velocity of the vehicle increases.
2. Drivers follow an 'intelligent' braking strategy (hence the model name). During normal driving situations decelerations are smooth, never going past some limit that depends on the individual driver's preference and decrease to zero when the target velocity is reached, or the vehicle comes to a complete stop. The model does have provisions for extreme situations where the deceleration can exceed the normal limits to avoid danger. This behavior is required to make the model collision free.

3. Transitions between different driving conditions are smooth (i.e. – between freely accelerating and following a leading vehicle). This provision ensures that the time derivative of the acceleration function is continuous.

The mathematical realization of these properties is given by the following equations (M.~Treiber & A.~Kesting, 2013; Treiber et al., 2000):

$$\frac{dv_\alpha}{dt} = a^\alpha \left[1 - \frac{{v_\alpha}^\delta}{v_0} - \left(\frac{s^*(v_\alpha, \Delta v_{\alpha,\alpha-1})}{s_\alpha}\right)^2\right] \quad (2)$$

$$s^*\left(v_\alpha, \Delta v_{\alpha,\alpha-1}\right) = s_0 + \max\left(0, vT + \frac{v_\alpha \Delta v_{\alpha,\alpha-1}}{2\sqrt{ab}}\right) \quad (3)$$

The first part of equation (2): $1 - \frac{{v_\alpha}^\delta}{v_0}$ describes the freely accelerating behavior of the driver. If there are no vehicles or obstacles ahead they accelerate freely towards their target velocity, with the acceleration gradually reducing all the way to zero when the actual velocity equals the target. The second part of equation (2) implements the effect of leading vehicles or obstacles on the driver's acceleration $\left(\frac{s^*(v_\alpha, \Delta v_{\alpha,\alpha-1})}{s_\alpha}\right)^2$. This ratio is the difference between the desired safe distance gap and the actual gap between the vehicle and the leader. As the actual gap between the vehicle and the leader grows the contribution of this part tends to zero, hence satisfying acceleration property 2.

Equation (3) defines the desired safe distance from the leading vehicle based on the current velocity of the vehicle and the difference in velocity between it and the leader. There is a static minimum gap that is always maintained, even at standstill, and a dynamic component that changes with velocity. The dynamic component has two parts, the headway time component that increases the safe distance requirement as the velocity of the vehicle increases, and the intelligent braking component that either increases or decreases the gap based on the difference in velocities between the two vehicles. For a more in depth derivation and review of the IDM the reader is encouraged to refer to the original paper and supporting book (M.~Treiber & A.~Kesting, 2013; Treiber et al., 2000).

Model Parameters

Parameter Overview

This section will focus only on the parameters for the IDM, since it was the model ultimately used to generate the results that are analyzed in the paper. The acceleration parameter (a) seen in Equations (2) and (3) defines the maximum acceleration for the driver (m/s^2). This is the maximum acceleration the driver will use and represents how fast a vehicle accelerates from standstill if there are no leading vehicles or obstacles. It is not meant to represent the maximum acceleration capability of the vehicle. The driver reduces their acceleration towards zero as they approach their target velocity. The speed of this reduction is controlled by the exponent parameter δ from Equation 2, which has no units. The desired safe distance is controlled by the minimum gap (s_0) and headway time (T), the units being meters and seconds respectively. The target, or 'comfortable' deceleration parameter (b) is the rate at which a driver slows down when approaching slower/stopped vehicles or obstacles (m/s^2) (M.~Treiber & A.~Kesting, 2013). Again, this parameter is not meant to represent the physical capability of the vehicle, or even the maximum deceleration the driver will use. In cases where there is a large delta between the driver and leader's vehicle velocity the actual deceleration will exceed this value to prevent collision.

All of these parameters have direct intuitive links to driver behaviors (the possible exception being the exponent δ). An aggressive driver may have a slightly higher value for acceleration and lower value for headway time. The same driver on different types of roads can be modelled with the same parameters, all that has to be adjusted is the target velocity (v_0). To simulate driver behavior in different conditions, or different types of drivers in the case of autonomous vehicles, these parameters are simply adjusted for the corresponding vehicle agent type.

Parameter Value Assignment

Since these parameter values define driver behaviours, they aren't something that can be derived mathematically or solved for analytically. Under ideal circumstances these parameters would be derived from real world data, taken in the area that is the target for simulation. This was not done for this project, so the values for the model that were calibrated by the original authors were used as a baseline for normal drivers under normal conditions, and these parameters were varied for different scenarios. See Table 1 for the values from the original paper (Treiber et al., 2000).

Table 1 - IDM Parameters

Parameter	**Calibrated Value from Original Paper**
Acceleration (a)	0.73 m/s^2
Deceleration (b)	1.67 m/s^2
Exponent (δ)	4
Time Headway (T)	1.6 s
Minimum Gap (s_0)	2.0 m

One parameter that wasn't taken from the original paper was target velocity (v_0). This value depends on the speed limit for the roadway and the behaviour of the driver. For the intersection simulation the value for roadway speed limit was set at 16.67 m/s (60 km/h), and the average target velocity set as a percentage of this depending on the scenario. The roadway speed limit for the freeway was set at 33.33 m/s (120 km/h), with the same target velocity variations. These values are typical values seen in Canadian cities on urban streets with intersections and freeways respectively.

Parameter Variations – Inclement Weather

One of the scenarios that was analyzed using this model was inclement weather. Specifically, rainy road conditions and winter road conditions (snowy/icy roads). In inclement weather both the capabilities of vehicles, and the driving strategy/behavior of the driver can change. Wet or icy roads reduce pavement friction, therefore reducing the capability of the vehicle to accelerate/decelerate (J.W. Hall, K.L. Smith, L. Titus-Glover, J.C. Wambold, T.J. Yager, 2009). The IDM model allows us to model this very easily simply by dividing the acceleration and deceleration parameters by a 'weather factor'. Deciding exactly what this 'weather factor' should be set at for rainy and snowy weather was the challenge. There are a lot of studies done on the effects of weather on driving, but most of them that were found during the literature review focused on how weather effects road safety (i.e. – number and severity of accidents). That being said, a study was found that modelled pavement friction changes due to bad weather, using this as a guideline the weather factor for rainy conditions was set at 1.7, and for snowy conditions it was set at 3.0 (Abdi, Rahmani, Saman, & Nasiri, 2018). This was setup as another parameter in the simulation runs so it can easily be adjusted to use the model to simulate more specific or empirically measured road conditions.

To model changes in driver behavior due to bad weather the target velocity and minimum gap parameters were adjusted. This was done to simulate the driver taking a more conservative approach when the weather is bad since they are aware of the reduced braking capabilities discussed in the previous section. The target velocity for each driver on the road will vary slightly, but for this simulation it was assumed that in rainy weather drivers reduced their target velocity by 5%, and by 10% in snowy weather (Kilpeläinen & Summala, 2007).

The minimum safe gap between vehicles was increased by 0.5 meters from 2.0 to 2.5 for rainy weather, and by 1.0 meter from 2.0 to 3.0 for snowy weather. There was anecdotal reference to increased following distances in the literature but no hard values, so these are values are assumptions, not based on real world measurements.

In the real world, not all drivers have the same target velocity. For this simulation it is assumed that the target velocity is based primarily on the speed limit for the roadway, but that it can vary with a normal distribution around that value. The normal distribution of velocities for drivers in these simulations was assumed to have a mean of the roadway speed limit, with a standard deviation of 10% of that speed. The minimum was hard capped at 60%, and the maximum at 150% to avoid extreme cases that could arise from the tail ends of the distribution that would represent extremely unlikely real-world conditions.

Parameter Variations – Green Light Interval

The traffic signals in the four-way intersection also act as agents in this model. Their behavior is varied by changing the green light intervals. Traffic flow is measured for a variety of different green light intervals to examine how changing this parameter can potentially improve traffic performance.

Dynamic control of traffic lights is possible using modern traffic management systems (Diakaki, Papageorgiou, Papamichail, & Nikolos, 2015; Zhao, Li, Wang, & Ban, 2016). There are multiple examples in the literature of people studying methods to improve traffic management by optimizing traffic signal light timings with respect to multiple traffic metrics (roadway usage, fuel efficiency, etc) (Brockfeld, Barlovic, Schadschneider, & Schreckenberg, 2001; Yulin, Peng, Lin, & Zhen, 2007; Zhao et al., 2016). All of the studies mentioned look at methods to improve traffic performance by implementing different traffic management strategies around signal intersection timing and intersection design. Some examples include the use of "green waves" where green light switching is delayed for successive intersections (Brockfeld et al., 2001), the implementation of random delays in green light switching (Brockfeld et al., 2001), using traffic data improve the physical layout of intersections (Yulin et al., 2007), and the use of vehicle to vehicle and vehicle to infrastructure communication to dynamically optimize signal timing with respect to travel delays and fuel consumption (Zhao et al., 2016).

In the model created in this project, weather is used as a variable to optimize traffic signal intervals on. The idea being that real time weather data could be fed to a traffic management control system and the signal timing changed dynamically based on current conditions. No literature was found that set out to do this, although a study was found looking at the instrumentation side of reporting weather based road conditions to a traffic management system (Haug & Grosanic, 2016).

Parameter Variations – Autonomous Vehicles

The second scenario that required model parameter variation was the introduction of autonomous vehicles into the driving population.

Since exact models for how autonomous vehicles are still very much proprietary trade secrets of the companies developing them, this information was not available for these simulations. Instead, parameter variations were extrapolated from the features that it is assumed that autonomous vehicles will have based on literature on the subject.

The first assumption that was made about autonomous vehicles is that their behavior will be more homogenous than human drivers (Liu, Guo, Taplin, & Wang, 2017). There will undoubtedly be multiple automaker brands that will market autonomous vehicles, and perhaps different behaviors between different models within these brands. That being said, it is assumed that because of the ability to more tightly control the behavior of autonomous vehicles that governing bodies will require them to follow the posted speed limits more closely than current human drivers do. For these simulations the target velocity of autonomous vehicles was still modelled as a normal distribution with the mean at the roadway speed limit, but with a standard deviation of only 1%, a hard minimum of 90% and hard maximum of 110%.

The second assumption that was made about autonomous vehicles is that they will require a smaller minimum safe distance than human drivers. The reasons for this are two-fold: 1) Autonomous vehicles should not suffer from distractions the same way human drivers do. They will be specially designed to monitor roadway conditions relevant to driving and should ignore other distracting information that it is sometimes difficult for humans to ignore (i.e. – cell phones). Due to this improved reaction time they can get away with a closer following distance.

2) Autonomous vehicles will have the capability to use inter vehicle communication with other autonomous vehicles on the road to determine the target velocity of their leading vehicles, and to be forewarned when their leading vehicles are going to change velocity (Fernandes & Nunes, 2010; Milanes et al., 2014).

This tight communication can allow for a platooning behavior where a group of vehicles can follow very closely together, increasing the density of vehicles on the road and therefor improving the overall efficiency of the roadway (Diakaki et al., 2015). In this project it is assumed this benefit cannot be realized from any potential communication between autonomous and human driver vehicles.

It can be stated that the second assumption described above is most useful in the case of a fully autonomous driver population where large platoons can form, but in general will contribute to the autonomous vehicles ability to keep a smaller minimum safe distance from its leading vehicle. This reduction in minimum safe distance requirement was modelled simply by changing the s_0 parameter from autonomous vehicle agents from 2.0m to 1.0m (but maintaining the constant increase of 0.5m and 1.0m in rainy and snowy weather respectively). For the freeway environment, this effect was also implemented as a reduction in headway time. This simulates the platooning behavior described above. Since it is assumed that autonomous vehicles will not be able to platoon with human driven vehicles, this headway time reduction had to be tied to the level of autonomous vehicles in the population. It was assumed that the headway time for autonomous vehicles in a fully autonomous population would be half of the human driver headway time, and this was scaled by the percentage of autonomous vehicles in the population (i.e. – at 50% autonomous vehicle penetration, the headway time is reduced by 25%). Ideally the autonomous vehicles would be able to recognize that the vehicle ahead of them was autonomous and platoon with them, but this functionality would have required major model modifications and was outside the scope of this project.

Model Development

Initial Work

The primary goal of this project was to develop an ABM that could be used to simulate traffic intersections. A secondary goal was to have a modelling platform that would allow expansion into other traffic environments (i.e. – freeways) using the same basic vehicle agents. A development platform was required that allowed the implementation of the vehicle agent behavior in a parametric way as described in the previous section, as well as the implementation of other secondary agents (i.e. – traffic signals) as needed. The ability to have multiple agent types with different behaviors is core to the ABM paradigm (Hanappi, 2017), but a software platform is required to implement this paradigm.

Writing a complete ABM system from the ground up was briefly considered, but quickly abandoned because of the large amount of work required that would move the focus from running actual simulations to building a simulation software tool. Also, there are multiple modelling software tools readily available on the market today, some of which are even open source. The first iterations of the intersection model were created using AnyLogic (Anylogic Company, 2015). This is a proprietary general-purpose ABM software package written in Java that had all the building blocks in place for creating the intersection model. The focus of AnyLogic is more in the domain of social science ABM's, but it does provide the capability to define continuous space environments where Agent velocities can be tightly controlled, allowing for the implementation of the acceleration behaviors of the GFM (at this time the switch to IDM had not been made yet). AnyLogic also allows implementation of agent behaviors using state diagrams, which greatly simplifies the implementation of traffic signal agents. The first version of the traffic intersection model environment can be seen in Figure 1.

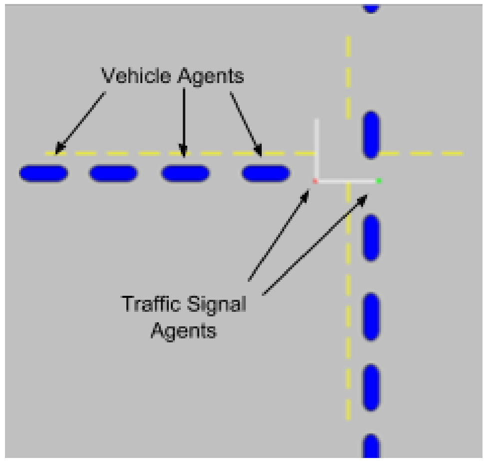

Figure 1 - AnyLogic Intersection Model Environment

Everything in the environment is roughly to scale for an average urban intersection. The width of each lane is three meters, which falls in the typical range for American roads, 2.7 to 3.6m (American Association of State Highway and Transportation officials, 2001).

The length of the vehicles is parametric but was always held at 5m throughout all the simulations. As vehicles pass through the intersection they are counted, and the total number that pass through during a simulation is used to calculate the vehicle flow. This is the metric used to evaluate the performance of the intersection, with higher flow rates being more desirable.

Model Implementation in SUMO

This model was used to do initial simulation runs with the GFM, but as time went on the decision was made to switch to the IDM for a more realistic description of driver behavior. Before re-writing the code to implement IDM behavior the use of AnyLogic was re-evaluated. Firstly, because the implementation of different acceleration models is time consuming, and because the addition of different road styles would be very time consuming since AnyLogic didn't implement simple behaviors like following a roadway, all of that had to be done from scratch.

The limitations of AnyLogic were not a problem for simple four-way intersection as shown in Figure 1, but the goal was to have a tool that could be used to model more complicated traffic situations in the future. For this reason, a search for a different software modelling tool was started. It should be noted that since this decision was made AnyLogic has added functionality specifically focused at traffic modelling that simplified roadway construction, but there is not sufficient vehicle agent behavior control to use it for a project like this.

Several different general-purpose ABM packages were investigated including Repast and Mesa. Both of these packages were attractive because they are open source, giving more flexibility to change parts of the code if necessary, but neither of them had any more built-in support for traffic simulation than AnyLogic did. The simulation package that was ultimately used was Simulation of Urban Mobility (SUMO) (Krajzewicz, Erdmann, Behrisch, & Bieker Laura, 2012). SUMO is an application specific, microsimulation package that provides specialized tools for creating road networks, defining traffic signal and vehicle agent behaviors. SUMO also has a built-in implementation of the IDM, simplifying the development of the model. SUMO allows for setting road speed limits as a property of segments in the road network, so you can have different speed limits in the same model. Vehicle target speed can be defined as a percentage of the roadway speed limit, and can be randomly assigned on a normal distribution, so the variation in driver target speed described in previous sections is easy to implement.

The environment for the intersection model was re-implemented in SUMO and it can be seen in Figure 2. Autonomous and human driver agents are given different colors to visualize the level of autonomous vehicle penetration (50% in this example).

SUMO allows the placement of virtual induction loops elements that collect flow and density information about the roadway, mimicking induction loop systems used on real roads. This data is output to XML files where it was analyzed using Python data science libraries Pandas (McKinney, 2010) and NumPy (Oliphant, 2006).

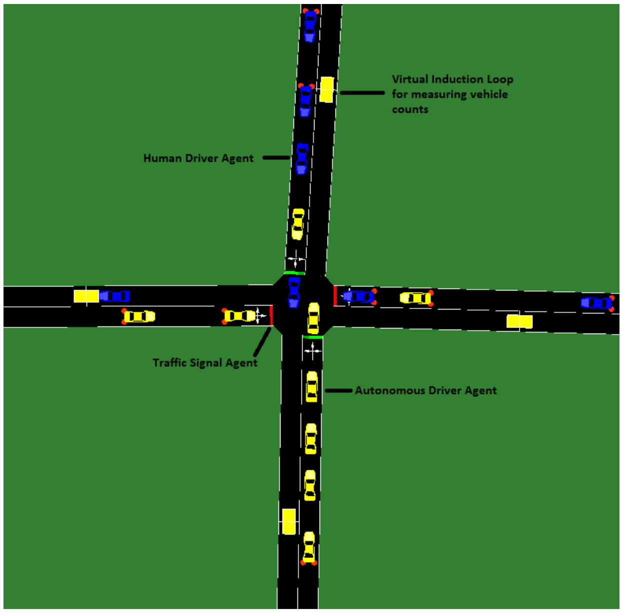

Figure 2 - SUMO Intersection Model Environment

The second type of roadway that was modelled in SUMO was a three-lane freeway with off and on ramps, seen in Figure 3. The same colouring for human vs. autonomous agents is used. The primary goal of this environment was to try and assess the impact of autonomous vehicles on freeway traffic flow. SUMO made it easy to add additional lanes, and on/off ramps. SUMO also handles the lane-changing behaviors to more realistically simulate a real-world driving scenario where faster drivers will overtake slower ones. SUMO has built in aggregate output recording capabilities which were used to capture the flow, speed and density for the segment of freeway between the on/off ramps.

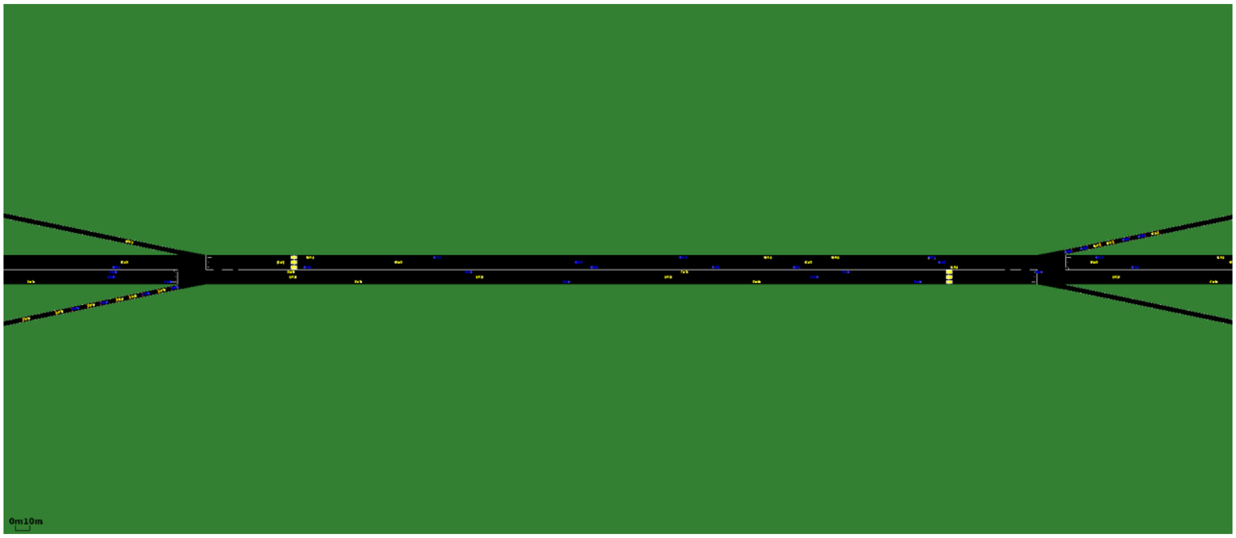

Figure 3 - SUMO Freeway Model Environment

For both of the road networks, the low-level driver behavior is described by the IDM. The second aspect of driver behavior that had to be modelled is the higher-level route planning behavior. In the four-way intersection environment, all driver routes were simply to maintain the direction they were travelling when they entered the simulation, driving directly through the intersection, no right or left turns. In the freeway simulations drivers entered the roadway on either the freeway itself, or one of the on-ramps. Vehicles would either drive straight through or exit on the off-ramp. None of the drivers that entered on the on-ramp exited at the off-ramp, since this would be a-typical driving behavior. All of these routes are defined in SUMO using XML files that allow specification of where the vehicles enter the road network and where they exit. As vehicles enter the freeway simulation environment their route is assigned probabilistically, with a large percentage of drivers remaining on the freeway the whole time and a smaller percentage using the ramps. These percentages are parameters of the model and are easily adjusted to see the effects of increased on/off ramp traffic.

Agent Behavior Variation Implementation

With the road network environment defined, low and high-level agent behavior implemented, and the ability to collect data out of the simulation for analysis, the next problem to solve was how to run large batch runs of simulations with variations on the parameters that define agent behavior. SUMO has a Python based extension called TraCI which allows the execution of simulations from a Python script, and the ability to modify some simulation parameters like traffic signal timings in real time. For model parameters that cannot be changed in real time, the general-purpose and XML libraries of Python were used to create the XML files that define low and high-level driver behaviors on the fly so multiple simulations can be run in a loop with the parameters being varied via Python.

Analysis and Discussion

Model Verification

The first step before using the model to analyze any real-world scenarios was to verify that the IDM implementation in SUMO was re-creating the results from the original paper.

In addition to this, velocity profiles for vehicles moving through the four-way intersection were plotted to ensure the movements were smooth, without any unrealistic jumps or sharp changes.

One of the velocity profiles from the original paper (Fig. 2 in that document) can be seen in Figure 4 - Velocity Profile from Original IDM PaperFigure 4, and the version created in SUMO can be seen in Figure 5. The three velocity profiles are all for a single vehicle driving on a 2.5km stretch of road, slowing down as they approach an obstacle at the end (as described in the original paper). The solid line in both figures is using the standard calibrated values from Table 1 for driving behavior parameters, the dotted line shows a much more aggressive acceleration behaviour ($a = 2.0\ m/s^2$), and the dashed line shows a much more aggressive braking value ($b = 5.0\ m/s^2$). Both of these figures show the same velocity profile, verifying that the IDM behavior in SUMO matches the original paper (at least for acceleration and deceleration, there were other tests done in the original paper not relevant to the situations being studied here). The authors of the original IDM paper verified/validated their model against empirical data, giving confidence that the simulation results generated using it will be a reasonable approximation for real world situations.

Figure 6 shows the velocity profiles of 10 vehicles going through the intersection simulation. This is not a test done in the original paper, but one that has been used in other car following model literature as a way to validate model performance (Jiang et al., 2001). The smooth, roughly bell shaped, curves show the vehicles accelerating smoothly towards their desired maximum velocity then decelerating down to stop at the stop light. They all accelerate away from the intersection out of the simulation. These results help to validate our intersection model setup. Full validation would require real world data that the model could be tuned to, but the goal here was to have a model that gave generic results that were a reasonable estimation of generic urban traffic, tuning to a specific geographical location was not the goal.

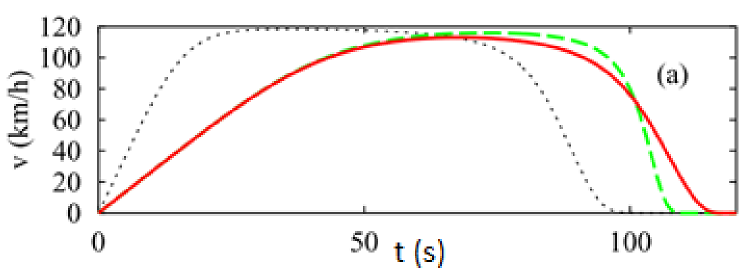

Figure 4 - Velocity Profile from Original IDM Paper, Fig 2 from (Treiber et al., 2000)

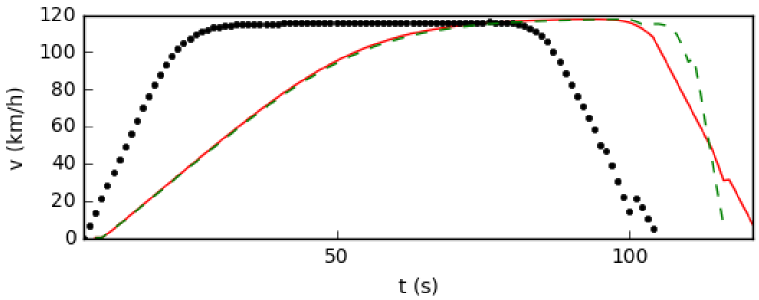

Figure 5 - Recreated Velocity Profile Using SUMO

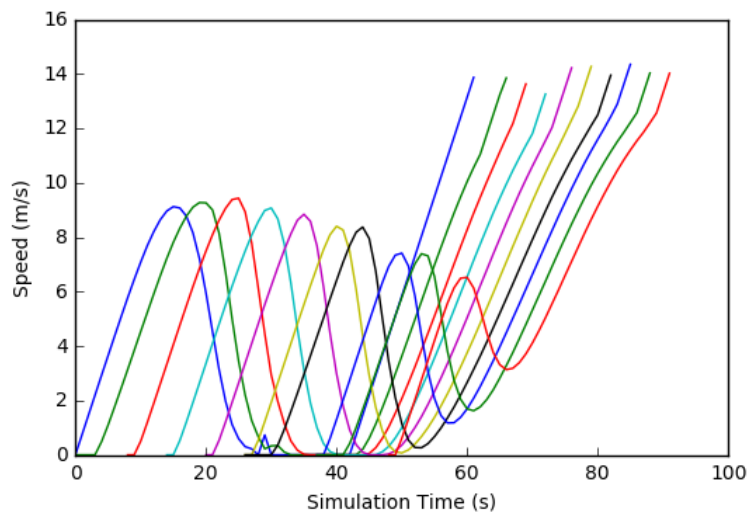

Figure 6 - Vehicle Velocities during Intersection Run

In Figure 6 each curve represents an individual vehicle accelerating towards a desired speed, then decelerating to stop for a red traffic signal. After the signal turns green all vehicles freely accelerate out of the intersection.

Effects of Signal Timing on Traffic Flow

Normal Weather

The first objective of this ABM project was to use the model to analyze the effect of changing the traffic signal timing on vehicle throughput in the intersection.

The simulation environment was populated with 100 vehicle agents coming from each direction (400 total) and allowed to run until all vehicles had passed through the intersection. This scenario was repeated with the green light interval varying from 10 seconds to 120 seconds, and with heavy traffic (vehicles arriving at the intersection constantly), moderate traffic (vehicles arriving at the intersection every 5 seconds and light traffic (vehicles arriving at the intersection every 10 seconds). Flow was measured in all four directions and averaged out, all lanes were given equal priority in the signal timing (the duty cycle of the green interval was 50%).

The results of the heavy traffic simulation runs suggest that as you increase the green light interval up from 10 seconds the vehicle flow increases, until it reaches a maximum and the total flow through the intersection begins to decrease as the green interval is increased beyond this optimal value. The maximum intersection flow rate was 451 vehicles/hour with a green interval of 60 seconds. There was a similar pattern for moderate traffic, with a slightly higher maximum intersection flow rate of 452 vehicles/hour at a green interval of 60 seconds. The results for light traffic suggest that total throughput slowly decreases as the green interval is increased. The maximum flow for light traffic was 343 vehicles/hour at a green interval of 15 seconds. The maximum flow rates for the different levels of traffic are summarized in Table 2. It is worth noting that the optimal green interval for flow in heavy/moderate traffic only reduced the flow during light traffic to 337 vehicles/hour, a decrease of approximately 1.5%.

These results agree with intuition since in heavy/moderate traffic as you increase the green on time vehicles spend less of their time accelerating/decelerating.

The decrease in flow after the maximum was somewhat unexpected but does make sense since if you allow enough vehicles to pile up at an intersection the flow will never reach a point where approaching vehicles don't have to slow down because of the congestion. The flow rate versus green interval for the three levels of traffic can be seen in Figure 7.

Table 2 - Maximum Vehicle Flows, Normal Weather

Level of Traffic	Vehicle Flow Rate (veh/hour)	Green Light Interval (s)
Heavy	451	60
Moderate	452	60
Light	343	15

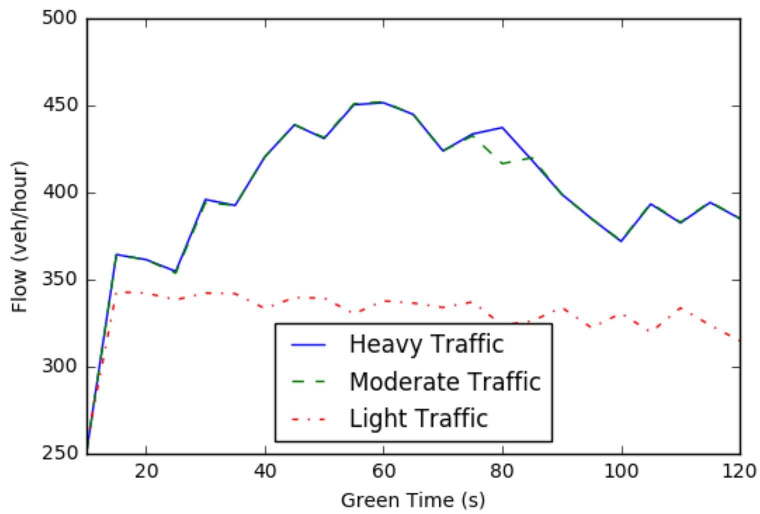

Figure 7 - Intersection Flow Rates, Normal Weather

Inclement Weather

The next objective of the traffic intersection model was to assess the impact of inclement weather on traffic flow and see if adjusting signal timings during bad weather could be used to recover some of the lost throughput. The three types of weather looked at in the model were normal weather (discussed above) as well as two types of inclement weather: rainy and snowy weather. The number of agents and green light timings for these types of weather was identical to the normal weather simulation runs.

The results from the rainy weather simulation runs can be seen below in Figure 8, with the maximum flow rates for each level of traffic summarized in Table 3 - Maximum Vehicle Flows, Rainy WeatherTable 3 Unlike normal weather simulations, the maximum vehicle flow rate comes with heavy traffic levels. The maximum value of 337 is 25% lower than normal weather conditions, indicating (as expected) that weather has a very significant impact on intersection traffic flow. The results suggest there is some benefit to increasing the green interval during bad weather as the maximum flow occurs at 65s instead of 60. The light traffic flow curve follows the moderate/heavy traffic curves much closer in rainy weather than it did in normal weather, suggesting that there isn't the same sacrifice in light traffic throughput when you increase signal timings in rainy weather (although the sacrifice in normal weather was small to begin with).

Table 3 - Maximum Vehicle Flows, Rainy Weather

Level of Traffic	**Vehicle Flow Rate (veh/hour)**	**Green Light Interval (s)**
Heavy	337	65
Moderate	336	65
Light	328	65

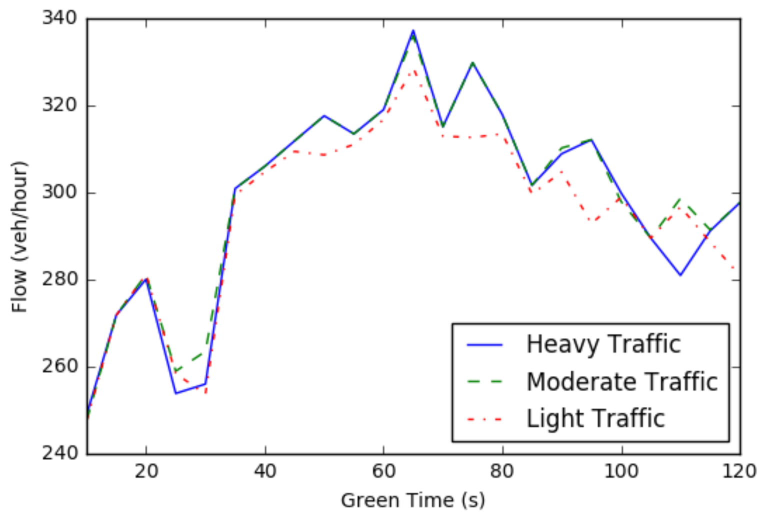

Figure 8 - Intersection Flow Rates, Rainy Weather

Snowy/Icy Weather

The final weather condition simulated was winter weather (snow and ice). The vehicle flow rate curves can be seen in Figure 9, and the maximum flow rates are summarized in Table 4.Table 4 – Maximum Vehicle Flows, Snowy Weather As expected, throughput is further reduced in snowy weather conditions. Interestingly the maximum flow rate is the same for all three levels of traffic. It takes the vehicles so long to slow down and speed back up again that even when vehicles arrive at a period of 10s the intersection permits just as many vehicles as if they show up continuously. At lower green intervals the intersection flow is unstable, jumping up and down before settling out around 50 seconds. This result corresponds to a scenario most winter drivers are familiar with. Light turns green, the leading vehicle has to wait for the intersection to clear, and then it takes a long time for vehicles to start flowing through the intersection. In this author's experience on winter roads, often only one or two vehicles will make it through an intersection. The maximum flow rate is 232 vehicles per hour, a 49%

reduction from normal weather, and a 31% reduction from rainy weather. 31% reduction from rainy weather. 31% reduction from rainy weather.

The maximum flow rate occurs at a green interval of 70s, up 10 seconds from normal weather and 5 from rainy weather, suggesting that small increases in green interval can help alleviate (in a small way) the effects of inclement weather on intersection flow rate reductions.

Table 4 – Maximum Vehicle Flows, Snowy Weather

Level of Traffic	Vehicle Flow Rate (veh/hour)	Green Light Interval (s)
Heavy	232	70
Moderate	232	70
Light	232	70

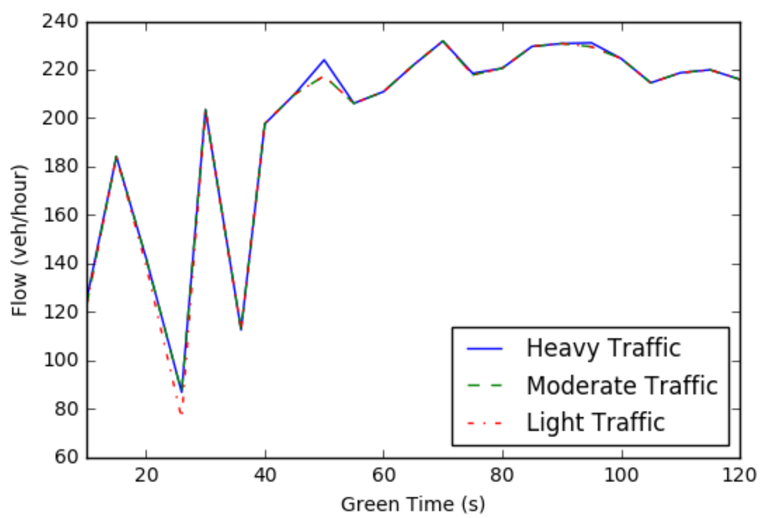

Figure 9 - Intersection Flow Rates, Snowy Weather

Effects of Autonomous Vehicles

Intersection Environment

The second scenario studied using this model was the introduction of autonomous vehicles into the population. Autonomous vehicles were introduced into the driving population in 10% increments to see how vehicle flow through the intersection would change as autonomous vehicles slowly mixed with human drives until ultimately all the vehicles on the road were autonomous agents. All other simulation conditions were kept the same as the previous section. The results of these simulations are summarized in Figure 10. The x-axis of the graph shows percentage of human drivers in the population. The graph shows a slow but steady decline in flow rates as the percentage of human drivers in the population increases. This pattern is similar for all levels of weather. The values in the graph are all for heavy traffic levels.

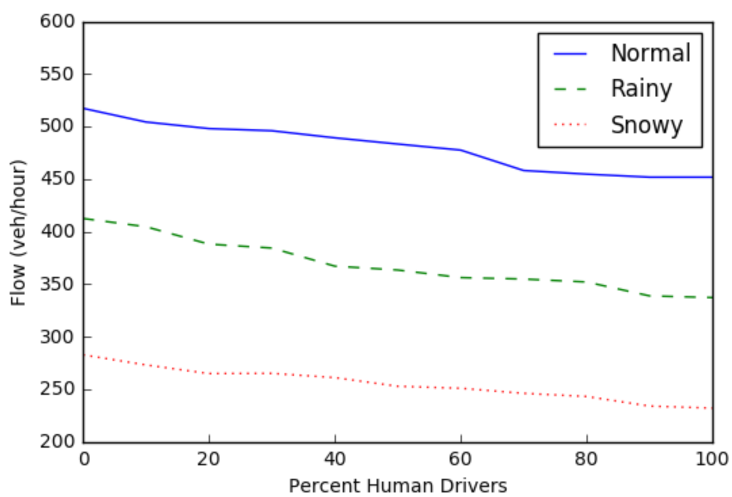

Figure 10 - Maximum Intersection Flow Rates

A condensed version of the maximum flow rate tables for the 100% autonomous driver population data can be seen in Table 5. The maximum intersection traffic flow is increased for all weather conditions, at all three measured levels of traffic. The fully autonomous population showed a 15% increase in maximum flow in normal weather, 22% increase in rainy weather, and 46% increase in snowy weather. The vehicle flow rate versus green interval can be seen in Figure 11, Figure 12, and Figure 13. The overall shape of these curves is similar to the human driver agent results, although the flow rates on the short green-on times in snowy weather are more stable with autonomous drivers than human ones.

Table 5 - Maximum Intersection Flow Rates, Autonomous Vehicles, All Weathers

Level of Traffic	**Vehicle Flow Rate (veh/hour)** **(Normal, Rain, Snow)**	**Green Light Interval (s)** **(Normal, Rain, Snow)**
Heavy	517, 412, 283	60,70,90
Moderate	508, 412, 281	60,70,90
Light	338, 337, 273	60,45,100

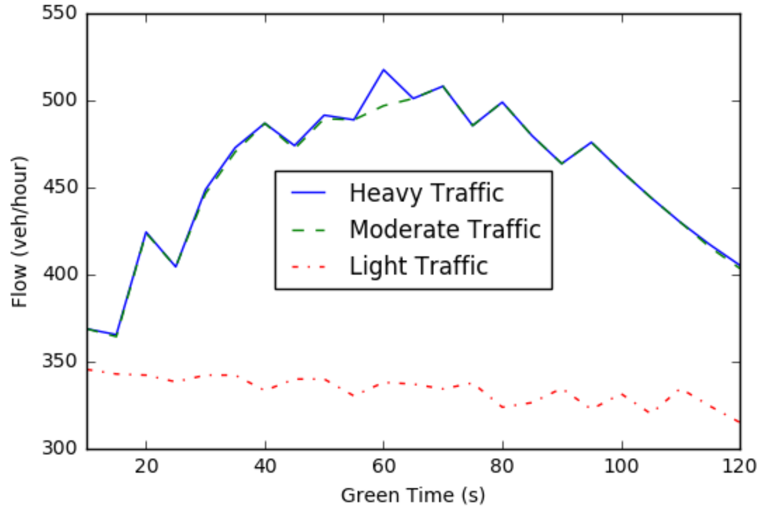

Figure 11 - Autonomous Vehicle Flow Rates, Normal Weather

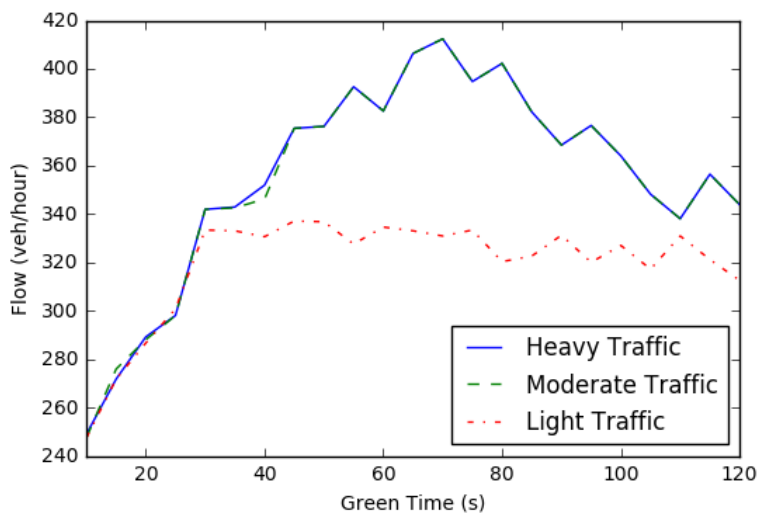

Figure 12 - Autonomous Vehicle Flow Rates, Rainy Weather

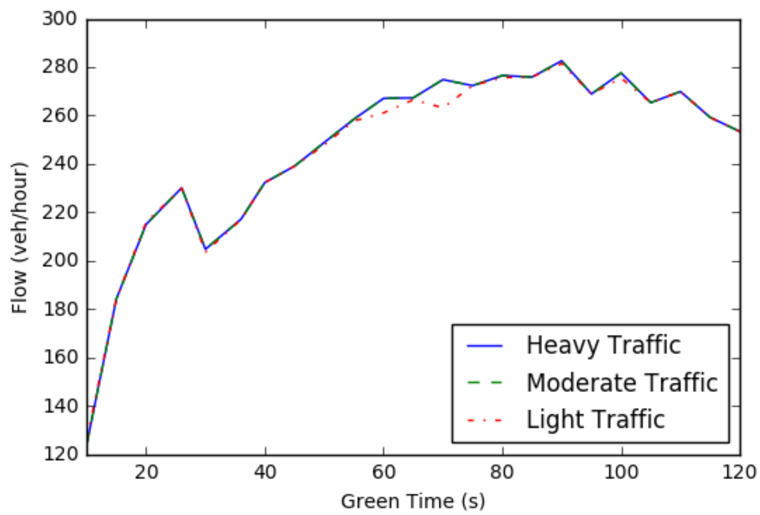

Figure 13 - Autonomous Vehicle Flow Rates, Snowy Weather

Freeway Environment – Straight Segment

The second environment where the effect of autonomous vehicles was investigated was the simple three lane freeway with on/off ramp. Three levels of traffic were used in these simulations, but they were defined by the number of vehicles entering the freeway segment per hour, as opposed to the arrival period used in the traffic intersection environment. Light traffic was set at 2000 vehicles/hour, moderate at 3000 vehicles/hour and heavy traffic at 6000 vehicles/hour. Autonomous vehicles were introduced at 25% intervals instead of 10% since the smaller steps were not required to see the overall change in traffic patterns as autonomous vehicles enter the population, and this saved simulation time. The first freeway scenario simulated the effect of autonomous vehicles entering the driver population on a straight stretch of freeway under normal weather conditions (no on/off ramp traffic).

For the freeway data analysis the average speed and vehicle density is also included since this gives more insight than the flow data alone for freeways, and is commonly used in the literature studying freeway traffic (*Highway Capacity Manual: Metric Units*, 2000).

The flow, speed, and density values versus human drivers as a percentage of the driver population can be seen in Figure 14, Figure 15 and Figure 16 respectively. The average speeds may seem low for a freeway with a speed limit of 120km/h, but keep in mind that the speeds are a space mean, so the slower vehicles spend more time on the road and contributed more to the average vehicle speed of the roadway. In light and moderate traffic, the vehicle flow is virtually unaffected by the introduction of autonomous vehicles into the population, but the density and speed are different. Autonomous vehicles travel at a higher speed on average, with a lower traffic density. This is an interesting result since the target headway time for autonomous vehicles is lower, leading to the expectation that there would generally be higher vehicle density for autonomous vehicles. The most likely explanation is that the tighter control of vehicle speeds reduces the amount of vehicle braking and lane changing, which reduces the clumping of vehicles that causes higher densities and reduces vehicle speeds. In the heavy traffic scenario, the vehicle flow rate increases as more autonomous vehicles enter the population. It increases faster in the 75%-100% autonomous vehicle penetration range, because the average headway time of the autonomous vehicles goes down as they have more vehicles to platoon with.

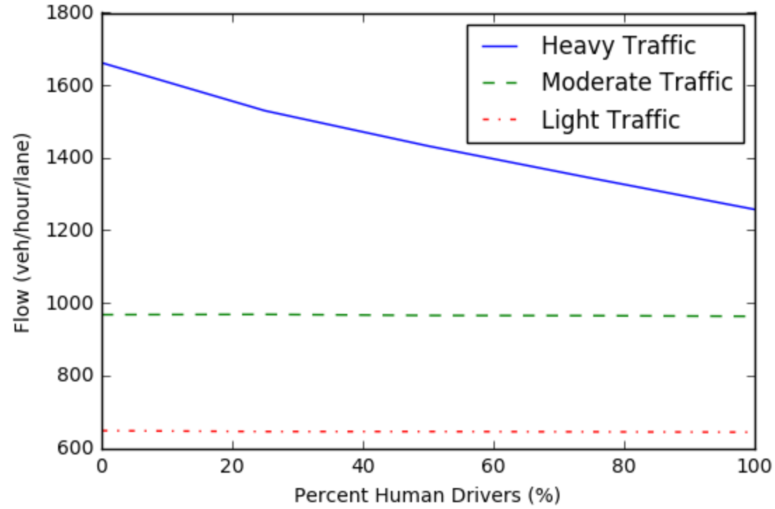

Figure 14 - Freeway Traffic Flow, Normal Weather

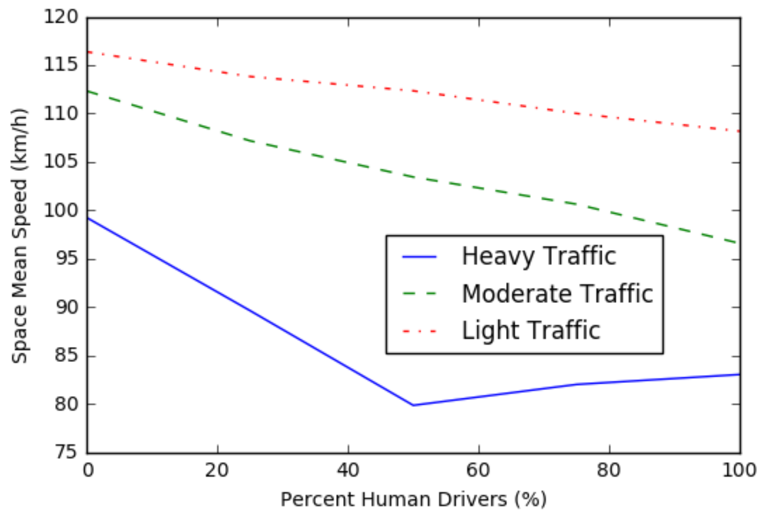

Figure 15 - Average Freeway Speeds, Normal Weather

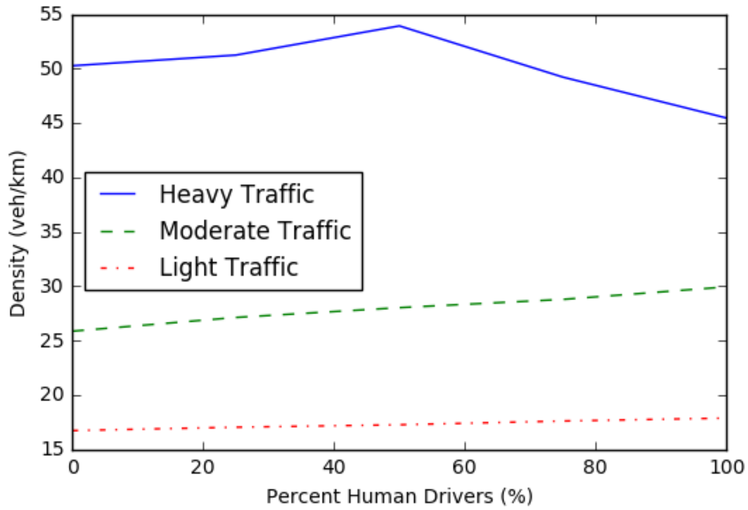

Figure 16 - Freeway Traffic Density, Normal Weather

Freeway Environment – Straight Segment, Inclement Weather

The straight segment freeway simulations were run again with the inclement weather conditions simulated in the signalized intersection environment. The same reductions in acceleration capability, target speed, and increases in minimum safe distance were used. The target headway times were not adjusted. The traffic flow, speed and density can be seen in Figure 17, Figure 18, and Figure 19 respectively. Similar patterns in traffic metrics appear as autonomous vehicles are introduced in rainy weather as were seen in normal weather. There is an 18% reduction in maximum freeway traffic flow during rainy weather.

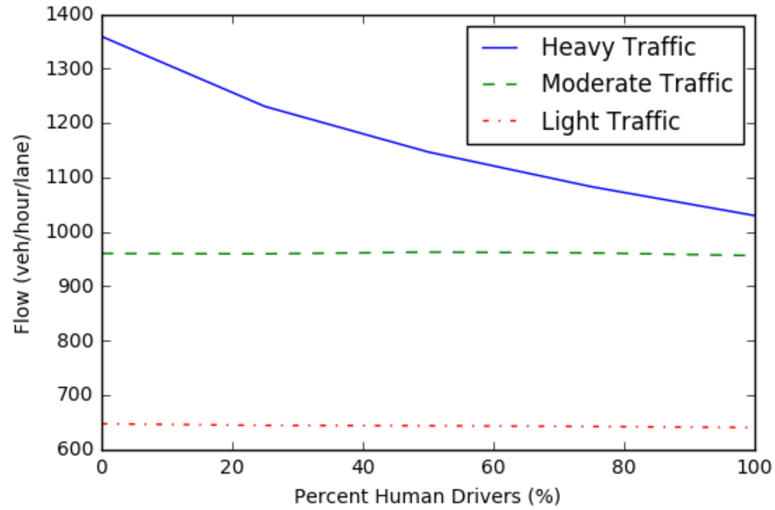

Figure 17 - Freeway Traffic Flow, Rainy Weather

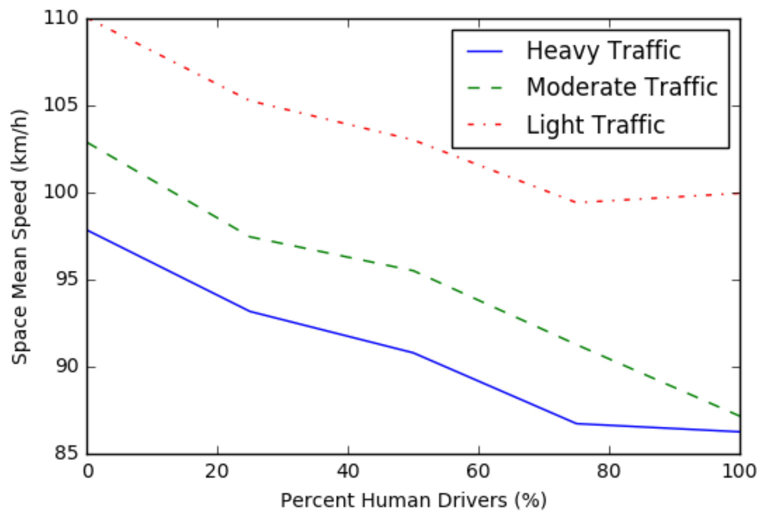

Figure 18 - Average Freeway Speeds, Rainy Weather

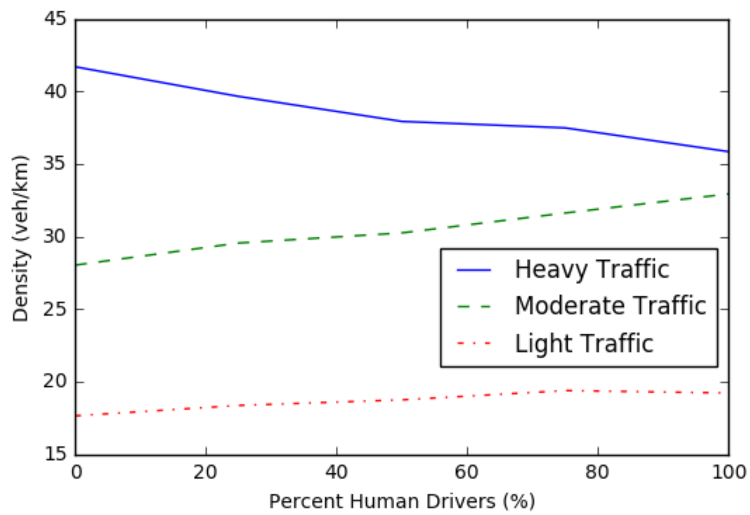

Figure 19 - Freeway Traffic Density, Rainy Weather

In snowy weather, the freeway traffic flow is further reduced as expected. The traffic flow, speed and density can be seen in Figure 20, Figure 21, and Figure 22 respectively. As with normal and rainy weather, the flow rates did not change significantly as autonomous vehicles entered the population under low and moderate traffic levels. Under heavy traffic when 40% or more of the population was human drivers the flow rate slipped below moderate traffic level, signifying a traffic jam. With less than 40% human drivers, the flow rates increase back above moderate traffic levels. This is due in part to the reduced headway time that allows for more vehicle throughput, but also because of the reduction in speed variation in autonomous vehicle populations. With less speed variation there are fewer braking reactions. Since acceleration and deceleration take longer under snowy conditions the speed homogeneity has a more pronounced benefit in this scenario. In snowy weather the maximum flow rate was reduced by 30% from normal weather conditions.

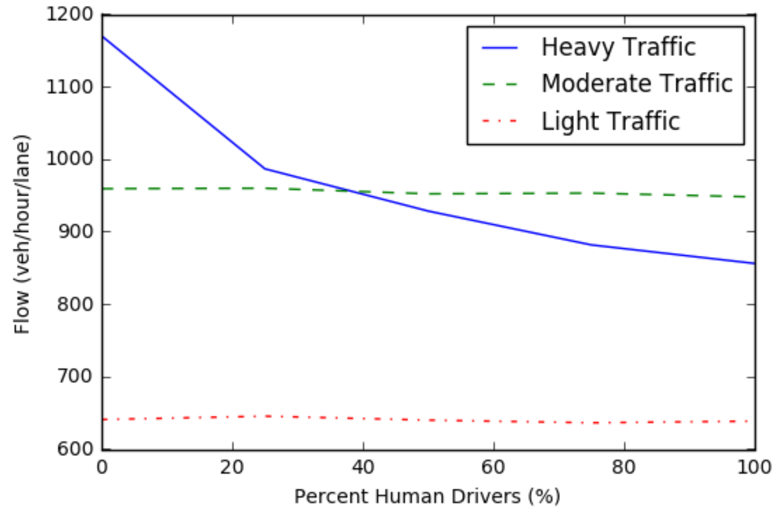

Figure 20 - Freeway Traffic Flow, Snowy Weather

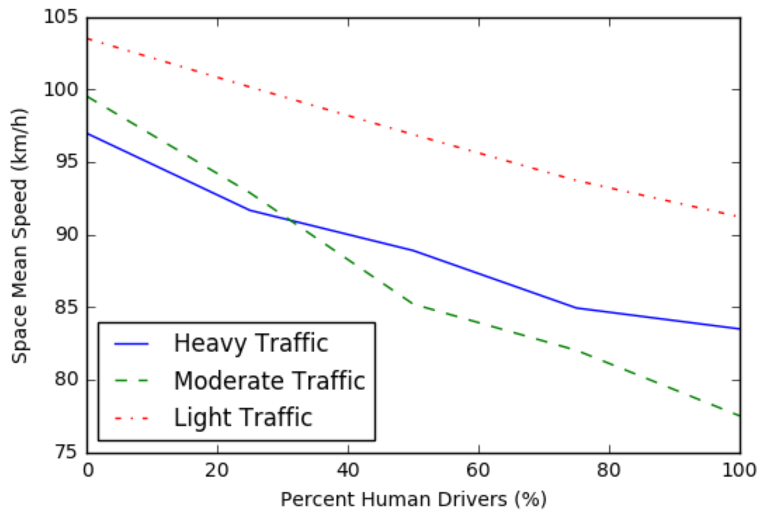

Figure 21 - Average Freeway Speeds, Snowy Weather

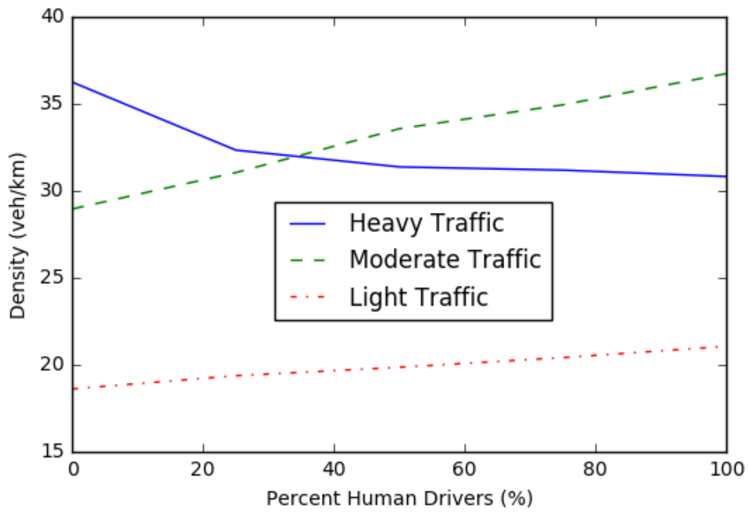

Figure 22 - Freeway Traffic Density, Snowy Weather

Freeway Environment – On/Off Ramp Effects

The last scenario simulated was the addition of traffic from the on and off ramps. Traffic routes were modified so that 10%, then 20% of drivers came from or exited on the ramps. This was split evenly between drivers that entered the freeway from the on ramp and continued on the main corridor and drivers that entered on the main corridor and exited on the off ramp. The focus on this analysis is the effect during heavy traffic since flow rates at low traffic levels stay fairly flat. This simulation was carried out under all three weather conditions. The traffic flow results for different levels of human/autonomous drivers in the three weather conditions can be seen in Figure 23, Figure 24, and Figure 25. The introduction of ramp traffic decreases traffic flow for all levels of human/autonomous drivers, in all weather conditions. This is not surprising since the on-ramp users have to merge into traffic which takes time and reduces the velocity of vehicles around them.

The off-ramp users have to do more lane changes to approach the ramp, and they have to decelerate to enter the ramp which has a lower speed limit (50km/h), causing braking reactions in the vehicles near them. The one result that is unexpected is that under normal weather conditions the 100% human driver population performs slightly better than all other populations except for 100% autonomous drivers. This is likely due to the specific set of speeds and headway times being advantageous for merging behavior, since this pattern was not seen again for the rainy or snowy weather simulations. The on/off ramp figures also help to illustrate how traffic flow increases more dramatically as autonomous vehicles become fully integrated into the driving population, the difference in flow rates between the subsequent levels of autonomous vehicles (0-100% from top to bottom) is more pronounced for the final jump (75-100%) than the others.

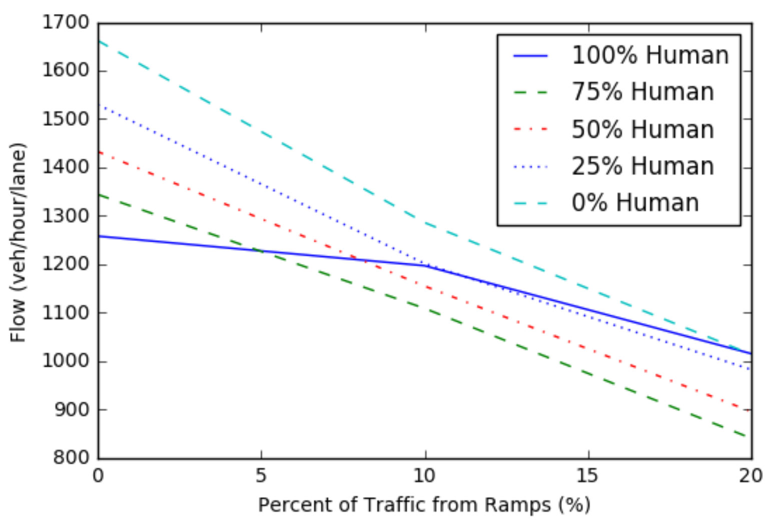

Figure 23 - Traffic Flow vs. Ramp Traffic Contribution, Normal Weather

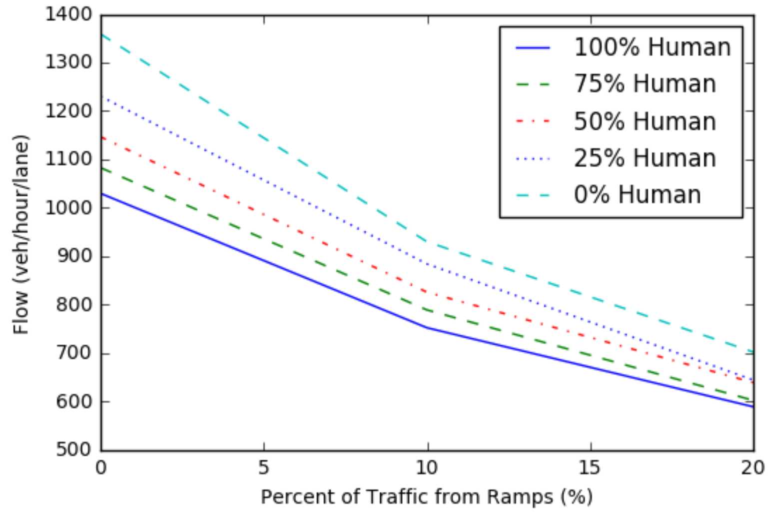

Figure 24 - Traffic Flow vs. Ramp Traffic Contribution, Rainy Weather

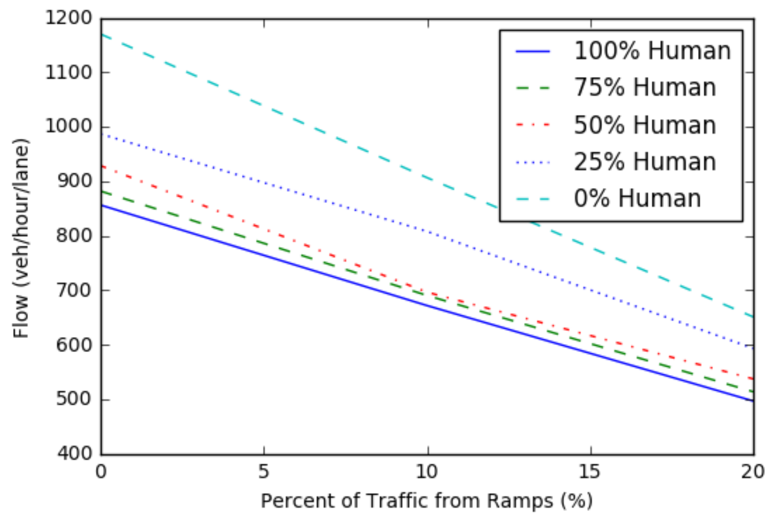

Figure 25 - Traffic Flow vs. Ramp Traffic Contribution, Snowy Weather

Conclusions and Future Work

In conclusion, this thesis has summarized the development, implementation, testing and analysis of an Agent-Based Model for vehicle traffic through a basic intersection, as well as a typical stretch of freeway. The development of the model was discussed including the background on the underlying mathematical models, initial testing and development in AnyLogic, and the final transition to SUMO. The methodology for verifying that the low-level driver behavior described in the original IDM paper was being re-created by SUMO was outlined.

After verification of the model was complete, the first scenario the model was used to analyze was basic intersection traffic under normal weather conditions. The results suggest that we can increase vehicle throughput in an intersection by increasing the green interval, but there is a limit to these gains, and they actually begin to decrease if the green interval is too long. This was an interesting result because the idea behind increasing the green interval was to reduce the overhead of acceleration and deceleration time when vehicles are not moving at their target speed. The initial hypothesis was that this overhead would continue to reduce the more that green-on time was increased, perhaps with diminishing returns. The simulations suggest that if you increase the green interval too high, the intersection gets so congested with arriving vehicles that a steady state flow where vehicles are moving at their target speeds can't occur or doesn't occur for as long as at lower green interval values.

The second scenario investigated was the effect of two different types of inclement weather on traffic flow through the basic intersection, rainy and snowy conditions. To simulate these conditions driver acceleration/deceleration capabilities were decreased, and their behaviours modified slightly.

The simulation data suggested that the maximum flow during rainy weather was reduced by 25%. The actual impact of rainy weather conditions on driving capability will vary a lot in different types of rain, different geographical regions where driver behaviours can be different for a variety of reasons, as well as many other peripheral factors, so the value of 25% could shift up or down significantly in a real word scenario. That being said, the simulation does suggest that in general rainy weather will have a major impact on intersection traffic flow, and therefore have a major impact on traffic in urban environments with a lot of intersections. This result is not surprising as it matches intuition for anyone who has driven in these conditions. Also, the simulation results agree with results determined from study of real world data (Datla, Sahu, Roh, & Sharma, 2013).

The goal of this project was not to confirm that inclement weather reduces traffic flow, but this result gives more confidence in the validity of the model. One of the goals was to see if we can use the model to suggest ways to improve throughput in these weather scenarios. The simulation results suggest that improved performance in inclement weather may be achieved by modifying the green light interval based on current weather, something that can be done very quickly from a remote traffic center using modern technology (Diakaki et al., 2015). The results of the simulation suggest that increasing the green interval will give us a small increase in flow since the maximum occurs at 65s instead of 60. At 60 second green-on time in rainy weather the flow rate is 319 vehicles/hour, so this adjustment results in a modest 6% gain, but any alleviation in heavy traffic is helpful.

Under snowy weather conditions the traffic flow was decreased again. The maximum flow achieved was 232, a reduction of 49% from normal weather, and 31% from rainy weather.

Again, the simulation suggests that raising the green-on time up from normal weather will help to increase flow (max flow occurred at 70 seconds). The flow rate at 60 seconds in snowy weather was 211 vehicles /hour, so by increasing the green-on time the flow rate was increased by 10%. This is a more significant result than the rainy weather result, and to anyone with winter weather driving experience a 10% increase in vehicle throughput at congested intersections would be much appreciated.

After the inclement weather signal timing focused simulations were run, the focus changed to autonomous vehicles. As expected the introduction of autonomous vehicles increased throughput at intersections. The increase was steady as the populations mixed together. The more interesting result was that the increase in throughput increased dramatically with normal, rainy and snowy weather (15%, 22%, 46% gains respectively with autonomous vehicles). This was not the expected result since their accelerations are scaled by the same factor, and the autonomous agent’s advantage in holding a tighter gap was reduced for the inclement weather scenarios. The autonomous vehicles always had a one-meter gap advantage, but as a percentage of the human driver gap this increased (50% of the human minimum gap distance in normal weather, 60% in rain and 67% in snow). It is hard to know how accurate these values will turn out to be once autonomous vehicles start appearing in cities, but since the model is parametric in nature it can continue to be adapted moving forward as more information about how autonomous vehicles perform becomes available.

In the straight segment freeway environment three levels of traffic were simulated (low, moderate and heavy), under normal, rainy and snowy weather conditions. Autonomous vehicles were inserted into the driver population to see how they affected traffic flow, speed and density.

Under normal weather conditions, with low and moderate levels of traffic, autonomous vehicles did not have a noticeable effect on traffic flow. There was an increase in average speed and reduction in traffic density which may indicate a more pleasant rider/driver experience. Under heavy levels of traffic, the flow rate increased from 1258 vehicles/hour with all human drivers to 1662 vehicles per hour with all autonomous divers (an increase of 32%). It should be noted that this increase in flow is primarily caused by the 50% reduction in headway time assumed for autonomous vehicles. If safety regulations, driver discomfort with small headway times, or technical limitations prevent autonomous vehicle manufacturers from realizing these headway time reductions then these increases in traffic flow due to autonomous vehicles is unlikely.

Unlike the intersection simulation environment, autonomous vehicle flow improvements were generally flat under inclement weather conditions (32% for rainy, 37% for snowy). It was assumed that the reduced headway times for autonomous vehicles would be maintained through different weather conditions. It is conceivable (perhaps even likely) that autonomous vehicles will be programmed to increase their headway times during inclement weather more than human drivers currently do. If that is the case, then these flow rate improvements on freeways would disappear and may even be reduced with autonomous vehicles. The trade-off goal would be less freeway accidents due to bad weather, which many might agree would be more beneficial to society than higher traffic flow.

For the simulation runs that added vehicle traffic that used the on/off ramps the traffic flow steadily decreased as more vehicles used the ramps. This is the expected result since the merging behavior required to use these ramps cause a reduction in vehicle speeds and increased lane changing, reducing the overall efficiency of the roadway. The introduction of autonomous vehicles did not improve performance of the on/off ramps.

With regards to autonomous vehicles, as more information becomes available about their driving behavior, and as governments start to form policies about what kind of safeguards will be required on their behavior, this information can be added to the autonomous agent's behavior to better simulate their potential impact on traffic.

There are too many potential extensions to this model to list all of them as future work. Some areas of focus that would be interesting include the extension of road networks to include multiple intersections and more complex driver routes to better simulate large scale urban traffic. SUMO has utilities that allow for the creating of road networks from GIS maps, so this extension could be done on a specific city or area of interest. If available, local driving data could be used to better tune the driver behavior parameters. Using the parameter variation methods discussed in this thesis this extension could be used to optimize traffic signal timings to current roadway conditions, and to simulate changes to the road network and evaluate their effect on traffic. Overall, the primary objective of studying the use of a traffic simulation based on the ABM paradigm was successful, and there is significant potential to continue to extend the model to more complicated environments (larger roadways), introduce additional agents (pedestrians, other vehicle types) and additional connections between agents in the simulation (vehicles that communicate with traffic signals, or traffic signals that communicate with each other to coordinate signal timings, for example).

Literature Cited

Abdi, A., Rahmani, O., Saman, A., & Nasiri, A. (2018). Effect of Adverse Weather Conditions on Vehicle Braking Distance of Highways. *Civil Engineering Journal*, *4*(1).

American Association of State Highway and Transportation officials. (2001). *A policy on geometric design of highways and streets*. Washington, D.C.

Anylogic Company. (2015). Anylogic [Computer Software]. Chicago, IL.

Brockfeld, E., Barlovic, R., Schadschneider, A., & Schreckenberg, M. (2001). Optimizing traffic lights in a cellular automaton model for city traffic. *Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, *64*(5), 12. https://doi.org/10.1103/PhysRevE.64.056132

Chandler, R. E., Herman, R., & Montroll, E. W. (1958). Traffic Dynamics: Studies in Car Following. *Operations Research*, *6*(2), 165–184. https://doi.org/10.1287/opre.6.2.165

Datla, S., Sahu, P., Roh, H.-J., & Sharma, S. (2013). A Comprehensive Analysis of the Association of Highway Traffic with Winter Weather Conditions. *Procedia - Social and Behavioral Sciences*, *104*, 497–506. https://doi.org/10.1016/j.sbspro.2013.11.143

Diakaki, C., Papageorgiou, M., Papamichail, I., & Nikolos, I. (2015). Overview and analysis of Vehicle Automation and Communication Systems from a motorway traffic management perspective. *Transportation Research Part A: Policy and Practice*, *75*, 147–165. https://doi.org/10.1016/j.tra.2015.03.015

Fernandes, P., & Nunes, U. (2010). Platooning of autonomous vehicles with intervehicle communications in SUMO traffic simulator. *IEEE Conference on Intelligent Transportation*

Systems, Proceedings, ITSC, 1313–1318. https://doi.org/10.1109/ITSC.2010.5625277

Goodwin, L. (2002). Weather impacts on arterial traffic flow. *Mitretek Systems Inc*. Retrieved from http://ops.fhwa.dot.gov/Weather/best_practices/ArterialImpactPaper.pdf

Hanappi, G. (2017). Agent-based modelling . History , essence , future. *PSL Quarterly Review, 70*(283), 449–472.

Haug, A., & Grosanic, S. (2016). Usage of Road Weather Sensors for Automatic Traffic Control on Motorways. *Transportation Research Procedia*, *15*, 537–547. https://doi.org/10.1016/j.trpro.2016.06.045

Helbing, D., & Tilch, B. (1998). Generalized Force Model of Traffic Dynamics. *Physical Review*, *58*(1), 133–138. https://doi.org/10.1103/PhysRevE.58.133

Highway Capacity Manual: Metric Units. (2000). Transportation Research Board.

Hoogendoorn, S. P., & Bovy, P. H. L. (2000). Continuum modeling of multiclass traffic flow. *Transportation Research Part B: Methodological*, *34*(2), 123–146. https://doi.org/10.1016/S0191-2615(99)00017-X

J.W. Hall, K.L. Smith, L. Titus-Glover, J.C. Wambold, T.J. Yager, Z. R. (2009). *Guide for Pavement Friction*. https://doi.org/10.17226/23038

Jiang, R., Wu, Q., & Zhu, Z. (2001). Full velocity difference model for a car-following theory. *Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, *64*(1), 4. https://doi.org/10.1103/PhysRevE.64.017101

Kilpeläinen, M., & Summala, H. (2007). Effects of weather and weather forecasts on driver behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, *10*(4), 288–

299. https://doi.org/10.1016/j.trf.2006.11.002

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker Laura. (2012). Recent Development and Applications of SUMO - Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements*, *5*(3–4), 128–138. Retrieved from http://sumo.sourceforge.net/

Liu, Y., Guo, J., Taplin, J., & Wang, Y. (2017). Characteristic Analysis of Mixed Traffic Flow of Regular and Autonomous Vehicles Using Cellular Automata. *Journal of Advanced Transportation*, *2017*. https://doi.org/10.1155/2017/8142074

M.~Treiber, & A.~Kesting. (2013). *Traffic Flow Dynamics*. Springer.

McKinney, W. (2010). Data Structures for Statistical Computing in Python. *Proceedings of the 9th Python in Science Conference*, *1697900*(Scipy), 51–56. Retrieved from http://conference.scipy.org/proceedings/scipy2010/mckinney.html

Metz, D. (2018). Developing Policy for Urban Autonomous Vehicles : Impact on Congestion. *Urban Science*, *2*(33). https://doi.org/10.3390/urbansci2020033

Milanes, V., Shladover, S. E., Spring, J., Nowakowski, C., Kawazoe, H., & Nakamura, M. (2014). Cooperative adaptive cruise control in real traffic situations. *IEEE Transactions on Intelligent Transportation Systems*, *15*(1), 296–305. https://doi.org/10.1109/TITS.2013.2278494

Oliphant, T. E. (2006). *Guide to NumPy*.

Treiber, M., Hennecke, A., & Helbing, D. (1999). Derivation, properties, and simulation of a gas-kinetic-based, nonlocal traffic model. *Physical Review E - Statistical Physics, Plasmas,* *Fluids, and Related Interdisciplinary Topics*, *59*(1), 239–253. https://doi.org/10.1103/PhysRevE.59.239

Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested Traffic States in Empirical Observations and Microscopic Simulations. *Physical Review*, *62*(2), 1805–1824. https://doi.org/10.1103/PhysRevE.62.1805

Ye, L., & Yamamoto, T. (2018). Modeling connected and autonomous vehicles in heterogeneous traffic flow. *Physica A: Statistical Mechanics and Its Applications*, *490*, 269–277. https://doi.org/10.1016/j.physa.2017.08.015

Yulin, C., Peng, Z., Lin, M., & Zhen, G. (2007). Multi-Phase Signal Setting and Capacity of Intersections. In A. Schadschneider, T. Pöschel, R. Kühne, M. Schreckenberg, & D. E. Wolf (Eds.), *Traffic and Granular Flow'05* (pp. 419–425). Berlin, Heidelberg: Springer Berlin Heidelberg.

Zhao, J., Li, W., Wang, J., & Ban, X. (2016). Dynamic Traffic Signal Timing Optimization Strategy Incorporating Various Vehicle Fuel Consumption Characteristics. *IEEE Transactions on Vehicular Technology*, *65*(6), 3874–3887. https://doi.org/10.1109/TVT.2015.2506629