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Problem Chosen

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2017
MCM/ICM
Summary Sheet
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Type a summary of your results on this page. Do not include
the name of your school, advisor, or team members on this page.

We present a model of traffic in the greater Seattle area to understand how an increasing frequency of self-driving cars will change traffic dynamics in the area. We apply a **two-component micro/macro traffic simulation** to data for portions of **Interstates 5, 90, 405, and State Route 520** to consider the impact of autonomous vehicles on regional traffic flow. We consider 0%, 10%, 50%, and 90% autonomous traffic.

Our micro model is designed to make predictions about the impact of self-driving vehicles on fundamental traffic dynamics and employs a **cellular automata approach**, inspired by the work of Nagel and Schrekenberg, to model interactions between a number of independent vehicles on a road. In this simulation, vehicles exhibit simple following behavior and experience occasional random deceleration events. We introduce a distinction between self-driving and human-driven cars, where autonomous vehicles exhibit **more uniform cruising speed** compared to human drivers and can **follow safely at a much closer distance** compared to human drivers.

Using this micro-level simulation, we predict a relation between traffic speed and traffic density for traffic with a varying composition of autonomous vehicles. Our macro model employs a system of ordinary differential equations to investigate the flow of traffic between segments of road in the region of study. We assess the impact of self-driving traffic composition on performance of the regional highway network at peak and average traffic loads, measuring trip times along each major highway and between a representative set of regional destinations. The travel time predictions of the macro model are **compared to archived travel time data** from the the Washington State Department of Transportation (WSDOT).

These models, in conjunction, facilitate insightful study of how different percentages of self-driving cars on the motorways change traffic flow under heavy and light traffic conditions. The quantitative accuracy of our macro model is observed to decline significantly with increasing traffic loads. Nevertheless, the results of our study demonstrate clear qualitative trends that inform our recommendations. Although our macro model does not make quantitatively accurate predictions, we observe a trend indicating that **at high traffic densities, traffic delays decrease with increasing percentages of self-driving cars** on the road.

Analysis of our micro model reveals that assigning traffic lanes for the exclusive use of autonomous vehicles can be a boon to traffic flow efficiency. When the concentration of self-driving cars rises to above 5%, our micro model predicts that it becomes advantageous to **implement at least one ``self-driving-car only" lane** in roads with 3 or more lanes. Under some circumstances, this strategy has the potential to result in **reduced travel delays for human-driven and autonomously controlled vehicles alike**.

Team 57313
Mathmodelingland, WA

Jay Inslee
Office of the Governor
PO Box 40002
Olympia, WA 98504-0002

January 23, 2017

Dear Governor Inslee,

We write to you concerning your request for an analysis of the **impact of self-driving cars** on popular roadways in Thurston, Pierce, King, and Snohomish counties. This letter summarizes our exploration of how traffic dynamics on **I-5, I-90, I-405, and State Route 520** will change as the percentage of self-driving cars on these roads increases.

It is becoming increasingly likely that commercially available **self-driving, cooperating cars** will appear on roadways within the next decade. These cars will play an important role in determining the overall traffic patterns observed in the Puget Sound region. We approach understanding the impact of self-driving cars on traffic in the greater Seattle area with two models. First, we examine fundamental traffic dynamics with a discrete cellular automata simulation, which considers the effects of self-driving cars on traffic at the **micro** level, and then we apply these results to a **macro model specific to the Puget Sound region**.

Our preliminary results suggest that the introduction of self-driving cars to the motorways in question will **increase traffic flow when there is any effect at all**. This result is encouraging in that we project that self-driving cars will will reduce traffic delays encountered by motorists on the crowded highways of the region. We are confident that our model provides a **reasonable *qualitative* forecast** of the impact of self-driving cars on motorways.Our simulation approximates current traffic patters on popular routes (e.g. Federal Way to Seattle) to within 10% accuracy for most trips at average traffic volume. However, at higher traffic density, this model is far less accurate at simulating travel times, and a more detailed traffic model should be commissioned before quantitative predictions are taken seriously. In short, the simplifying assumptions that made the rapid delivery of this report possible necessitate that this **preliminary investigation be interpreted cautiously**. For example, we have not explored the psychological effects that the presence of self-driving cars will have on other motorists, the patterns of continuous change in traffic load on Seattle-area roads over the course of a day, the ways that inclement weather conditions will affect all forms of traffic, and a number of other considerations that may be more significant than we understand at present.

The results of our study lead us to believe that self-driving cars will affect traffic positively or not at all for average traffic flow. At higher traffic volumes where traffic delays begin to be encountered, we observe a trend that increasing percentages of self-driving cars lead to reduced travel time for everyone, although this reduction is not extreme (perhaps a half hour delay reduced by ten minutes). We also note that although this result is consistent with what our expectations, the reduced accuracy of our model at high traffic volumes calls this result into question. Our simulation suggests that when self-driving cars impact traffic flow at all, **they improve roadways for everyone**, not only for the owners of self-driving cars. We believe that this observation has important policy recommendations implications.

First and foremost, this study indicates that policy designed to enable self-driving cars to naturally integrate into the sections of Interstates under investigation **will not negatively affect driving conditions**. Furthermore our micro model predicts that, with a percentage of self-driving cars as low as 5% on moderately crowded roads, it is advisable to **designate a "self-driving-cars only" lane**. Such a lane is only beneficial to traffic flow on roads at least three lanes wide. We recognize that such autonomous-only lanes may be politically sensitive and that factors not included in our models may affect the performance of such lanes in reducing traffic, so we strongly encourage that policy to create these lanes be **enacted on a trial basis** to assess its feasibility.

Please do not hesitate to direct any further inquiries regarding the contents of this letter to our communications office. We would like to thank you for consulting with us, and we remind you that our firm is now well-equipped to provide similar impact studies on other roadways in a fraction of the time.

Regards,

Traffic Impact Analysis Team (57313)

Silence of the Jams

The Effects of Self-Driving Cars on Traffic Patterns in the Puget Sound Region

Team # 57313

January 23, 2017

Contents

Summary Sheet

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Further study of the potential effects of autonomous vehicles on urban traffic is necessary. Our analysis does not address important questions related to self-driving cars that could have huge impacts on traffic conditions in the Seattle metropolitan area, such as the impact of autonomous technology on the total number of vehicles on the road and the temporal distribution of traffic loads. Further modeling refinement is necessary at the macro level to make rigorous quantitative predictions about the impact of autonomous vehicles on regional traffic patterns; our model excludes many potentially significant factors such as accidents, road-closings, inclement weather, and aggressive drivers, to name but a few. Nonetheless, our model rigorously demonstrates that including significant proportion of self-driving cars on the road impacts traffic dynamics and suggests that such changes in traffic composition might meaningfully, although not totally, reduce the traffic congestion experienced by Seattle motorists.

1 Introduction

1.1 Motivation

With the continual rise of urbanization, the logistics of driving in metropolitan areas are an ever-pressing concern. In the Seattle metropolitan area, traffic jams, which occur regularly during weekday rush hours, are of particular concern. In 2015, Seattle was ranked 7th in the nation for the worst traffic conditions for auto commuters [2]. The cost of traffic is no mere inconvenience – it has a high economic, environmental, and quality of life price. Seattle's auto commuters are estimated to lose 63 hours a year to traffic delays, which are estimated to cost each commuter $1491 per year. In aggregate, 62,136,000 gallons of fuel are wasted each year in Seattle due to traffic delays, contributing to pollution and climate change. The net cost of traffic to the city is estimated at $3295 million annually. [2].

Engineers can attempt to ameliorate traffic congestion by adding extra lanes to busy freeways; however, there is a growing incentive to consider how self-driving cars will impact traffic[3]. With an annual growth rate hovering at 2%, Seattle roadways are quickly becoming more crowded, and given the concentration of tech corporations in the region (such as Google), it is likely that the greater Seattle area will be the first to see a rise in the percentage of self-driving cars on the road. We hope to understand how self-driving cars will affect traffic on Interstates 5, 90, and 405, as well as on State Route 520. A successful model will provide us with an understanding of the impact of self-driving cars, which in turn will inform road design and policy changes to better facilitate transportation.

1.2 Literature Search

Mathematical models of traffic can generally be classified as either discrete or continuous. In an extensive analysis of traffic models, one author estimates that in the past 50 years, researchers across many fields have suggested nearly 100 different ways of modeling traffic. [4] While a comprehensive review of each of these models is impossible, the ones we found most useful merit some discussion. We began by reproducing Kai Nagel and Michael Schreckenberg's cellular automata model of single-lane traffic [1], which gave us insight into the traffic modeling process and enabled us to collect traffic flux data for generic traffic flow. We applied these results to a model that we independently developed based on the guiding principles presented in Fowkes and Mahony's *An Introduction to Mathematical Modeling.*

In the course of our research, we also found Kachroo and Sastry's *Traffic Flow Theory* text [5] to be a useful resource for evaluating the results of our model. Although their various PDE models did not lend themselves to adaptation to account for self-driving cars, we were able to reproduce the flux-versus-traffic-density curves for the Greenshield and and Greenberg models that appear in Kachroo and Sastry's work, which we used as a metric for success of our fundamental traffic model. It would be interesting to compare our results to a PDE model that incorporates self-driving cars.

One of the most prevalent traffic phenomena that appears in research concerns "phantom traffic jams,"—traffic back-ups that happen even when nothing obstructs traffic flow—which **occur when human drivers act imperfectly**. In particular, Helbing identifies *overcorrection* and *chain reaction* as two ways that mathematical traffic models successfully simulate these phantom traffic jams [4]. We used this information to determine reasonable ways of modeling self-driving cars as distinct from human-driven cars.

1.3 Terminology

Some of the following terminology has been adapted from the problem statement.

- A **mile-marker** is a roadside marker that measures distance along the road from a fixed point.
- A **road segment** is any portion of road between two consecutive mile-markers.
- The **average daily traffic (ADT)** is the average number of cars per day driving on the road.
- The **increasing direction** is Northbound for N-S roads and Eastbound for E-W roads. The **decreasing direction** is the opposite of the increasing direction.

1.4 Hypotheses

Before describing our model, we discuss our hypotheses for how self-driving, communicating cars will affect traffic flow. We take on good faith that by the time self-driving cars are road-ready, they will (1) consistently have shorter event-response time (such as the time it takes to suddenly brake) than a human and (2) have better situational awareness (knowledge of traffic patters well-ahead and well-behind them) than a human. In addition, we do not account for the changes in traffic engendered by inclement weather, although according to an article in *The New York Times*, self-driving cars do not yet have the capacity to reliably navigate rain and snow conditions [6]. Based on these qualitative assumptions, we hypothesize that increasing frequencies of self-driving cars will:

1. reduce the travel time of going from A to B on busy roadways
2. decrease the variability of traffic flux across road segments
3. reduce the frequency of phantom traffic jams

2 Overall Assumptions

- We assume that the density of traffic on a road segment is constant and evenly spread across all available lanes. We also neglect the inefficiencies in traffic flow introduced by lane-changing.
- We assume that traffic is divided evenly between increasing and decreasing directions on roadways.
- We assume that "all roads are created equal." That is, interstates, highways, state routes, etc. are not treated differently.
- Furthermore, we assume that all roads are flat and straight, not changing in altitude or direction.
- Our model treats only major highways in the Puget Sound area: I-5, I-90, I-405, and SR 520.

- Our model neglects intersections between major highways, treating each as an independent stretch of road.
- We assume that highway conditions on the boundaries of the Puget Sound region are wide-open.
- We assume self-driven cars will randomly slow down with half the probability that a human would.
- We assume that a near-equilibrium traffic distribution is reached at both peak and normal traffic loads.

3 Variables and Definition of Standard Conditions

3.1 List of Variables

3.1.1 Micro Model

- v_i: the velocity of the ith car
- g: the minimum allowable distance between a car and the car ahead.
- p: the probability that a car will randomly decrease in velocity.

3.1.2 Macro Model

- D_i, units [miles]: the distance of the ith road segment
- N_i, units [cars]: the total number of cars on the ith road segment
- V_i, units [miles/hour]: the velocity of cars on the ith road segment
- F_i, units [cars/hour]: the flux of cars on the ith road segment
- N_{Li}, unitless: the number of lanes on the ith road segment
- L_i, units [miles]: the distance of "lane miles" on the ith road segment
- ΔC_i, units [cars/hour]: the rate at which cars drive onto the ith road segment (or off the $(i-1)$th road segment)
- ρ_i, units [cars/mile]: the effective density of cars over the total length of lanes present ith road segment
- $\hat{\rho}_i$, units [cars/mile]: the density of cars on the ith road segment, neglecting the presence of multiple traffic lanes

3.2 Definition of Standard Conditions

When running our simulations, we defined the following set of standard conditions:

3.2.1 Micro Model

- The maximum velocity for cars was set to 5 units.

3.2.2 Macro Model

- On average, 8% of the daily traffic volume occurs during peak travel hours. Thus, we model non-peak traffic conditions as having a traffic load equivalent to ADTC and peak traffic conditions as experiencing a traffic load equivalent to 192% ADT.

- The nominal speed limit for all of the roads we use in our model is 60 miles per hour. We assume that traffic leaves the system at the end of each highway at 50 miles per hour.

4 The Model

Our modeling efforts are divided into two main levels: macro and micro. Our micro model, a discrete cellular automata model inspired by [1], predicts the relationship between traffic density and traffic speed. This model is used to predict how this relationship between traffic density and flow rate will change with different concentrations of self-driving vehicles on the road. Our macro model, a system of ordinary differential equations, considers how the relationship between traffic density and traffic speed will affect regional traffic patterns in the Puget Sound area. This model ultimately makes predictions about expected travel time between regional destinations of interest.

4.1 Micro/Discrete Model

To see how the fundamental diagram changes as the number of self-driving cars increases, we set up a cellular automata model based on work by Nagel and Schrekenberg. In their original model, each car follows three rules at each time-step However, to model the effects of self-driving cars, we used the following modified rules.

1. **Acceleration**: The ith car moving with velocity v_i will increase its velocity by 1 so long as the car ahead is greater than $v_i + g$ or $v_i + g$ units away, where $g = 2$ for a human driver, and 1 for self-driven car.

2. **Slowing down**: If the car ahead is instead j units away with $j \leq v_i$, the velocity will decrease to $j - g$ or 0 if $j - g < 0$.

3. **Randomization**: Every car has a probability p of randomly decreasing their velocity by 1. For human-driven cars $p = 0.1$, and for self-driven cars, $p_s = 0.05$.

Once the velocities for every car is updated, each car is then moved ahead by v_i units. The density was calculated by counting the number of times a car lands on the center cell of the track, while the flux is calculated by counting the number of times a car passes through the center cell.

4.2 Using the Micro Model to Inform the Macro Model

Having developed a micro model, we need to extract useful density and velocity information to run the macro model. We do this by fitting our data from the micro model to a simplification of the curve shown in Figure 1, which we have adapted from [7]. The curious reader can find a more in-depth explanation of this fit in Dym's text. Our micro model data fits the red curve; however, for the sake of more efficient computation, we have chosen to apply a linear fit between the points (ρ_{crit},v_{max}) and (ρ_{max}, 0). This linear fit was inspired by Greenshield's model of the relationship between traffic flow and traffic speed [5]. Using this fit, we can determine the relationship between traffic density (ρ) and flow speed (v) in our macro model.

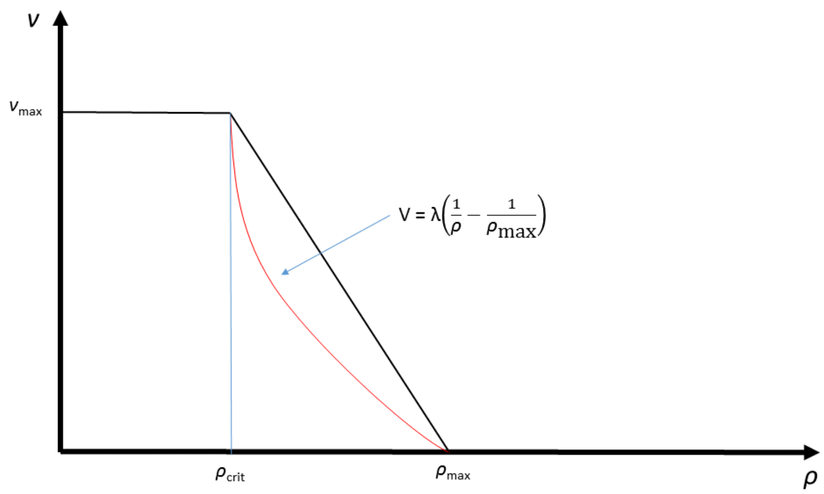

Figure 1: Original (in red, from [7]) and simplified flux curves illustrating speed-density relationship.

Our micro model predicts the following ρ_{crit} values for differing proportions of self-driving traffic. (Note that no significant difference in ρ_{crit} was observed between 0% self-driving traffic and 10% self-driving traffic.)

ρ_{crit} versus self-driving traffic proportion		
0-10%	50%	90%
0.13	0.16	0.18

4.3 Macro/Continuous Model

Our model, at the most fundamental level, traces the evolution of the number of cars on the road. Before further developing our simulation, we must establish the following useful quantities for the ith road segment.

$$L_i = D_i \times N_{Li} \tag{1}$$

gives the "lane length" of the road. This essentially allows cars to distribute evenly across the number of lanes available on road segment i. We next calculate car density,

$$\rho_i = \frac{N_i}{L_i} \tag{2}$$

which we will use in computing the net car flux through the ith road segment, given as developed by Fowkes and Mahony in their text, *An Introduction to Mathematical Modeling*, to be

$$F_i = \rho_i \times V_i \tag{3}$$

We begin with a first-order differential equation for the rate of change in time of the total number of cars on the ith road segment. We assume that cars flow into each segment at the road-length density of traffic in the preceding segment and the velocity of cars at that segment. We assume that cars flow out of each segment at the road-length density of traffic in that segment and the velocity of cars at the next segment. For a visualization of an arbitrary internal road segment, see Figure 2. Additionally, we assume that cars enter or exit the segment at a constant rate determined by the difference in average traffic between the previous segment and the current segment. This gives the relationship:

$$\frac{dN_i}{dt} = v_i \times \rho_{i-1} - V_{i+1} \times \rho_i + \Delta C_i - \Delta C_{i+1} \tag{4}$$

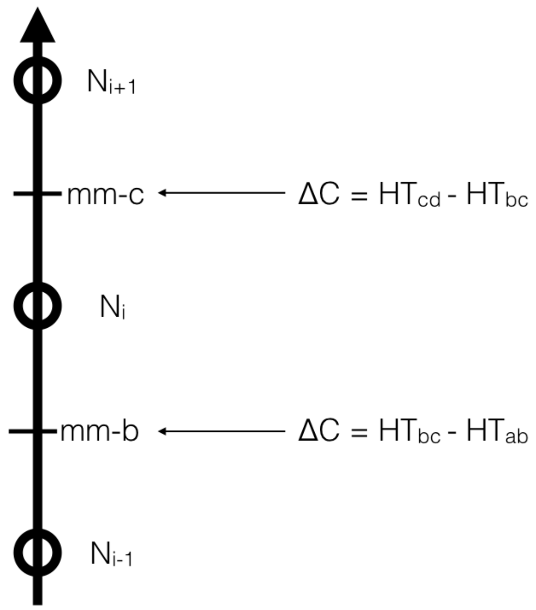

Figure 2: Schematic of ith road segment as a circular node. Here mm-x refers to mile-marker x, and ΔC keeps track of the cars that have entered or exited the road between nodes.

We model each direction of travel on each highway as a separate one-dimensional chain of highway segments. We do not model intersections between highways. For each highway system road segment at the beginning of a highway chain, we model cars as entering at a fixed rate C determined by the AADT recorded for the road segment. For each highway system road segment at the end of a highway chain, we model cars as leaving with traffic speed 50 miles per hour at the current traffic density of the end segment. This approach yields several systems of ordinary differential equations, which can be evaluated numerically. We use the Numpy `odeint` tool for this purpose [8].

We determine the traffic speed V at each segment from its density ρ using a smooth interpolation using B-splines of the density-flow rate predictions made by the discrete traffic flow model. To run the regional traffic model at peak traffic conditions, we simply scale the net traffic load uniformly across the system by 1.92, reflecting the observation that peak traffic volume observed over the course of an hour represents 8% of ADT on that segment.

$$T_{peak}/24 = 0.08 \times T_{avg}$$
$$T_{peak} = 24 \times 0.08 T_{avg} = 1.92 \times T_{avg}$$

ADT for each direction of each segment is one-half ADT reported for each segment, reflecting the assumption that traffic load at each segment is split evenly between the increasing and decreasing directions.

We run the simulation, beginning with initial conditions of a uniform distribution of traffic between road segments at a density of 25 cars per lane-mile, until it reaches a near-equilibrium state. Then, the density of traffic on each road segment is recorded. (For reported simulations, data on traffic density was collected after five hours of simulation time). This density information, coupled with the relationship between traffic density and traffic speed predicted by the micro model, yields travel time t between road segments i and j according to the following relationship

$$t = \sum_{n=i}^{j} \frac{D_n}{V(\rho_n)}$$

4.4 Micro/Discrete Model Validation

The results from the discrete model closely resembles results found in all of the literature we observed[5, 7]. Specifically, we looked to reproduce results from Nagel and Schrekenberg[1] as a starting point for modeling the effects of self-driving cars. We were also able to very closely fit our results to a model in Dym [7].

4.5 Macro/Continuous Model Validation

We validated our traffic model by comparing trip times for northbound and southbound traffic on popular stretches of roads to actual traffic data from the WSDOT website [9]. Specifically, we compared our model's predictions for travel times between a representative sampling of destinations of interest under average traffic conditions to WSDOT travel time data for non-peak traffic conditions. Our model made reasonable predictions under these conditions, often with error mostly below 20%. However, the macro model fares much more poorly at higher traffic levels, exhibiting significant error. Traffic jams – apparent through significantly lengthened travel time between destinations – do not manifest until quantitative traffic loads much beyond the traffic levels observed at peak traffic hours. At traffic loads approximately 50% greater than observed peak traffic and above, significant delays are observed on some highways, in particular I-5 South and I-405. This inconsistency may be due to the decision to model high-load traffic a static elevated demand upon highway infrastructure instead of a process where demand grows, peaks, and declines over time. Optimistic boundary conditions, which assume that traffic leaves the system mostly unimpeded may also contribute to the excess optimism of the model. Discrepancies in the translation of traffic flow predictions from the micro model to the macro model – such as the limited fidelity of the Greenshield-like linear fit to the micro model's predictions or distorted unitary scale in analysis of the micro model's predictions may also account for the discrepancy. Also, the neglect of traffic-blocking incidents such as breakdowns and accidents may why our traffic predictions are not as dire as WSDOT's 95% Worst Case Scenario travel times. Although further refinement this macro model is necessary for it to have quantitative relevance, we believe that it does have qualitative value in understanding the impact of the introduction of self-driving cars on Seattle traffic. Observed model predictions on travel times are tabulated below beside relevant reported WSDOT data.

Average Trip Times on Key Routes (Increasing/Decreasing)						
Origin	Dest	Road ID	Distance (miles)	Avg. Travel Data (min)	Avg. Travel Model (min)	% Error
Fed. Way	Seattle	5	22.2	22	22.6	3
Seattle	Everett	5	26.9	27	29.4	9
Seattle	Issaquah	90	15.7	16	14.9	7
Bellvue	Redmond	520	6.6	7	5.9	16
Renton	Bellvue	405	11.2	11	11.1	1
Seattle	Fed. Way	5	22.2	24	22.6	6
Everett	Seattle	5	26.9	27	29.4	9
Issaquah	Seattle	90	15.7	17	14.9	12
Redmond	Bellvue	520	6.6	8	5.9	26
Bellvue	Renton	405	11.2	11	11.1	1

Peak Trip Times on Key Routes (Increasing/Decreasing)								
Origin	Dest	Road ID	Distance (miles)	8:00 am Worst-Case Travel Data (min)	8:00 am Peak Travel Model (min)	% Error Peak Travel Model	1.6× Peak Travel Model	% Error 1.6× Peak Travel Model
Fed. Way	Seattle	5	22.2	69	22.7	67	25.1	64
Seattle	Everett	5	26.9	28	29.8	6	34.1	22
Seattle	Issaquah	90	15.7	22	14.9	32	15.7	29
Bellvue	Redmond	520	6.6	8	5.9	26	6.4	20
Renton	Bellvue	405	11.2	51	11.8	77	18.0	64
Seattle	Fed. Way	5	22.15	25	14.9	40	25.4	2
Everett	Seattle	5	26.94	89	30.0	66	76.8	14
Issaquah	Seattle	90	15.71	36	14.3	60	15.7	56
Redmond	Bellvue	520	6.62	11	5.9	46	6.4	42
Bellvue	Renton	405	11.2	27	11.8	56	19.3	28

5 Results

5.1 Micro Model

Our micro model predicts that an increase in traffic flow at elevated traffic densities will be observed comparing human-driven traffic to half self-driven traffic and a further increase in traffic flow at elevated traffic densities will be observed as the saturation of self-driving cars in traffic increases to 90%. These results can be seen in Figures 4 and 3, which display the relationship between traffic density and traffic flux and traffic speed, respectively.

Figure 3, which visualizes the relationship between traffic flux and traffic density, reveals that an approximately 40% increase in the maximal throughput of a road can can be realized through the widespread introduction of self-driving cars to the roadways. An approximately 20% increase in maximal throughput of traffic can be realized through 50% introduction of self-driving technology. Across different compositions of self-driving vehicles, flux is observed to be nearly identical up to ρ_{crit} for human-driven traffic, approximately 34 cars per lane mile. Beyond that density, flux of traffic with self-driving cars begins to exceed the flux of human-driven traffic– by a difference of constant magnitude for many density conditions. The magnitude of these difference greatly exceeds the variance that was observed in the data from stochastic simulation.

Figure 4 visualizes the relationship between traffic speed and density, for varying traffic compositions. Traffic speed is generally similar across the different traffic composition up to ρ_{crit} for human-driven traffic. Beyond this point, the traffic speed of human-driven traffic begins to decline noticeably at greater density levels. The speed of mostly and partially self-driving traffic begins to decline at slightly greater densities but still is greater than that of human-driven traffic, with mostly self-driving traffic tending to move faster than partially self-driving traffic. The predicted traffic speeds become more similar across the spectrum of traffic composition, again, at high traffic density.

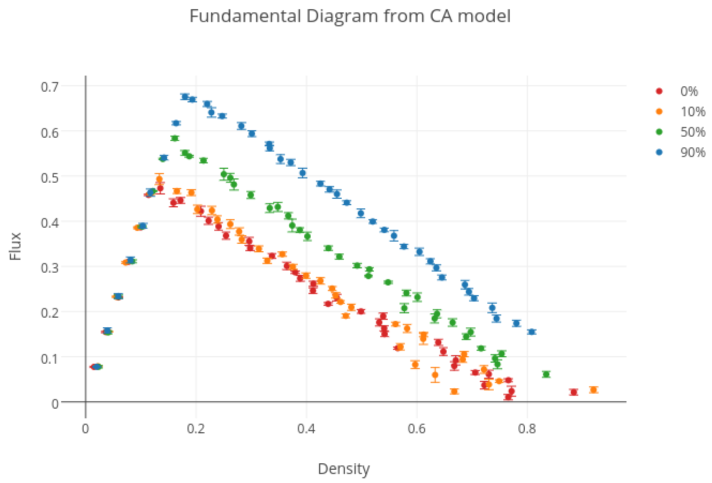

Figure 3: density and traffic flux data from our cellular automata model.

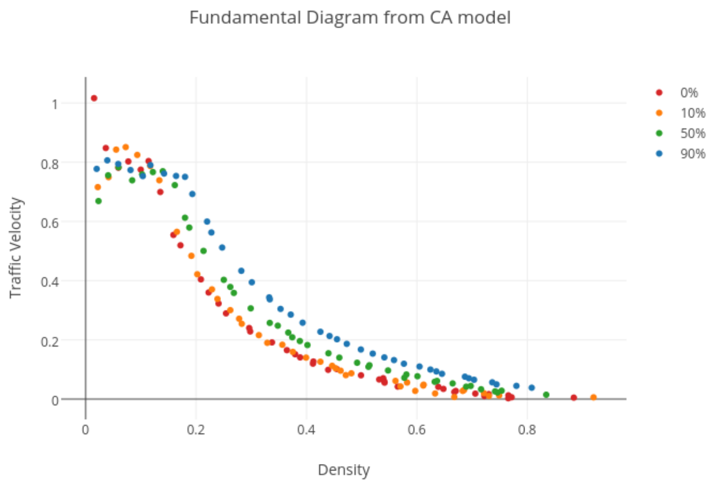

Figure 4: density and velocity data from our cellular automata model.
Each color represents different percentages of self-driven cars.

5.2 Macro Model

As mentioned in Section 4.5, the macro level model of regional traffic patterns does not correspond well to observed peak volume traffic conditions in a quantitative sense. However, the model makes qualitative predictions that may be of interest to policy makers.

As would be expected, the model predicts that the introduction of self-driving cars do tend to ameliorate traffic jams. Our micro model does not predict a significant difference in traffic behavior between 0 and 10% composition of self-driving cars in traffic. However, an effect on ρ_{crit} was observed when the prevalence of self-driving cars grew to 50% and, also, 90% (Section 4.5). This difference in ρ_{crit} predicted by the micro model was significant to observe reduction of traffic delays in the macro model. In all measured cases, the introduction of self-driving cars was observed to reduce or not affect travel times.

However, widespread introduction of the self-driving car is no silver bullet. Under heavy traffic loads, trip times did indeed increase with 90% self-driving traffic composition. For example, under average traffic conditions a trip down I-5 South is predicted to take 117 minutes. Under the maximum traffic load measured with no self-driving component of traffic, the duration of this trip increases to 169 minutes. However, at the maximum measured traffic load the trip is predicted to take only 145 minutes. Thus, the widespread introduction of self-driving cars has ameliorated – but not eliminated – traffic delays. Our model predicts that the introduction of self-driving cars has the potential to near completely eliminate – at most – minor traffic delays. Major traffic delays will likely not be completely eliminated by the introduction of self-driving cars, but – even under the conservative assumptions of our models – noticeably reduce traffic delays.

Predicted Effect of Percentage of Self-Driving Cars on Trip Times (Average Traffic)			
Road	Trip Times for 0-10% (min)	Trip Times for 50% (min)	Trip Times for 90% (min)
I-5 North	117.4	117.4	117.4
I-5 South	117.4	117.4	117.4
I-90 East	23.4	23.4	23.4
I-90 West	23.4	23.4	23.4
I-405 North	30.3	30.3	30.3
I-405 South	30.3	30.3	30.3
SR 520 East	12.8	12.8	12.8
SR 520 West	12.8	12.8	12.8

Predicted Effect of Percentage of Self-Driving Cars on Trip Times (Peak Traffic)			
Road	Trip Times for 0-10% (min)	Trip Times for 50% (min)	Trip Times for 90% (min)
I-5 North	118.0	117.5	117.4
I-5 South	118.4	117.8	117.7
I-90 East	23.4	23.4	23.4
I-90 West	23.4	23.4	23.4
I-405 North	31.2	30.7	30.5
I-405 South	31.2	30.7	30.4
SR 520 East	12.9	12.8	12.8
SR 520 West	12.9	12.8	12.8

Predicted Effect of Percentage of Self-Driving Cars on Trip Times (1.33× Peak Traffic)			
Road	Trip Times for 0-10% (min)	Trip Times for 50% (min)	Trip Times for 90% (min)
I-5 North	121.4	119.0	118.1
I-5 South	123.6	120.3	119.2
I-90 East	23.7	23.5	23.4
I-90 West	23.7	23.5	23.4
I-405 North	33.6	32.2	31.7
I-405 South	33.5	32.2	31.7
SR 520 East	13.0	12.9	12.8
SR 520 West	13.0	12.9	12.8

Predicted Effect of Percentage of Self-Driving Cars on Trip Times (1.5× Peak Traffic)			
Road	Trip Times for 0-10% (min)	Trip Times for 50% (min)	Trip Times for 90% (min)
I-5 North	125.2	121.3	119.5
I-5 South	146.6	134.05	127.0
I-90 East	24.0	23.6	23.5
I-90 West	24.0	23.6	23.4
I-405 North	35.9	34.1	33.1
I-405 South	35.8	33.9	32.9
SR 520 East	13.2	13.0	12.9
SR 520 West	13.2	13.0	12.9

Predicted Effect of Percentage of Self-Driving Cars on Trip Times (1.6× Peak Traffic)			
Road	Trip Times for 0-10% (min)	Trip Times for 50% (min)	Trip Times for 90% (min)
I-5 North	127.7	123.1	120.8
I-5 South	169.0	154.4	145.0
I-90 East	24.2	23.7	23.6
I-90 West	24.2	23.8	23.5
I-405 North	41.5	36.0	34.5
I-405 South	40.7	35.8	34.2
SR 520 East	13.4	13.1	13.0
SR 520 West	13.3	13.0	13.0

Predicted Effect of Percentage of Self-Driving Cars on Total Traffic Volume on Highways			
	0-10% Automated	50% Automated	90% Automated
Average Traffic	17657	17652	17652
Peak Traffic	34332	34062	33988
1.3× Peak Traffic	47741	46445	45922
1.5× Peak Traffic	57731	54784	53241
1.6× Peak Traffic	66119	61855	59754

6 Model Assessment

6.1 Micro Model Sensitivity Analysis

We performed a sensitivity analysis on our micro model, changing (1) the length of of the circular track and (2) the probability that a self-driven car will spontaneously slow down (all human-driven cars have a much higher probability of this "imperfect driving"). In the original paper from which we developed this model, the authors used a track length of 10,000 units. We were able to replicate the traffic effects that the authors observed using a track length of 500 units, although for our sensitivity analysis, we doubled the track length and observed an inconsequential change in the model output. Furthermore, the traffic-flow-versus-density plot changes insignificantly for variation of the probability that a self-driven car will slow down without reason. We set this parameter to 5% in our micro model, which we believe to be conservative for a self-driving car, but our sensitivity study confirms that increasing this value to 10% or decreasing it to 0% do not affect the model outcome. There are no other non-variable parameters in the model, so the results of this analysis suggest that we are using a robust, if simple, model.

6.2 Strengths

- By approaching the problem with both a micro and a macro model, we are able to apply relatively straightforward simulations to a more complicated problem.
- The model provides a simple, but reasonable, simulation of traffic, and given the success of our validation study, we are confident that it produces reasonable predictions for how self-driving cars will impact traffic, for which there is not yet any empirical data.
- The micro model produces flux, velocity, and density data that are consistent with previous research [1],[7].
- The model is not computationally intensive, so it does not require sophisticated hardware or specialized resources to replicate our work.
- The model produces travel times for normal traffic flow on popular routes that are typically accurate to within 10% of the actual average travel time.

6.3 Weaknesses

- The macro model does not give quantitatively accurate travel times for peak periods of travel.
- At extreme traffic loads, the distribution of traffic delays across the highway system does not closely resemble those reported by WSDOT.
- Our micro/macro model requires that we treat stretches of road between mile-markers as having constant density. This assumption precludes more nuanced modeling of traffic.
- In the micro model, self-driving cars are assigned a reduced probability of "imperfect driving," but they do not communicate with other cars on the road.
- The micro model is only validated insofar as the traffic flux-versus-density curve produced by our data is consistent with the literature. The micro model is not expressly compared to empirical data.

6.4 Improvements

- Our simulation produces good data for average traffic conditions, but is less reliable for peak traffic conditions. This is unfortunate since we are most interested in how self-driving cars will change traffic dynamics at high traffic densities. Our model should be modified to produce more representative values for travel time at peak travel times. This adjustment would lend credibility to predictions about the effect of percentage of self-driving cars on traffic patterns.

- The macro model should be extended to consider the effects of catastrophic incidents such as breakdowns and collisions on traffic dynamics, in particular, the ability of traffic flow to recover at different levels of self-driving traffic once such blockages are cleared.
- Our model would be stronger if it treated the road as a continuous stretch, rather than segments with uniform traffic density. We could perhaps use PDEs (rather than a system of ODEs) to provide this additional detail.
- While our micro model accounts for self-driving cars being more predictable, we should more precisely define and implement inter-car communication that would allow self-driving cars to know more about what the vehicles in its environment are doing.

7 Dedicated Lanes for Self-Driving Cars

The decision to use a dedicated lane for self-driving cars relies heavily on the percentage of cars that are self-driving. Here we derive a simple way to check if adding a dedicated lane or lanes would reduce traffic, and if so, how many lanes to add.

7.1 Variables

- c: the concentration or percentage of cars which are self-driven.
- ρ_s: the effective density of self-driven cars
- ρ_s^{cr}: the "critical density", or the density at which flux is maximized for self-driven cars
- ρ_h: the effective density of human-driven cars
- ρ_h^{cr} the "critical density" for human-driven cars.
- N_{LS} The number of lanes to be dedicated to self-driven cars.
- D_i^m: The maximum number of cars in a road segment of length D_i, i.e. bumper to bumper traffic.

7.2 Discussion

Recall that the "lane length" of the ith road segment L_i is defined as the product $N_{Li}D_i$ of the number of lanes and the length of the segment. Then the number of self-driven cars in this road segment is given by cN_i, while the number of human-driven cars is $(1-c)N_i$. Similarly, if N_{LS} lanes are dedicated to self-driving cars, $N_{Li} - N_{LS}$ lanes are dedicated to human driven cars. To normalize units of density we will use maximum number of cars in road segment i, D_i^m. We can then look at the effective densities for self-driven cars

$$\rho_s = \frac{cN_i}{D_i^m N_{LS}},$$

and human driven cars

$$\rho_h = \frac{(1-c)N_i}{D_i^m (N_{Li} - N_{LS})}.$$

By requiring that the effective densities of self-driving cars and human-driven cars be below their respective critical densities, in other words

$$\frac{cN_i}{D_i^m N_{LS}} \leq \rho_s^{cr}$$

and

$$\frac{(1-c)N_i}{D_i^m (N_{Li} - N_{LS})} \leq \rho_h^{cr},$$

we can solve for N_{LS}. Letting $\rho_e = \frac{N_i}{D_i^m}$, we get the following inequality:

$$c\frac{\rho_e}{\rho_s^{cr}} \leq N_{LS} \leq N_{Li} - (1-c)\frac{\rho_e}{\rho_h^{cr}}. \tag{5}$$

Our results suggest that even at high density traffic and a low concentration of self-driving cars, for three or more lanes, designating at least one lane for self-driving cars will reduce overall traffic.

8 Recommendations

- Our result, most simply stated, is that the more self-driving cars there are, the better traffic will flow. This being the case, our model suggests that policy should support the accessibility of safe, reliable self-driving cars to consumers.
- Our model predicts that while the introduction of self-driving cars may eliminate minor traffic delays but, at best, will only reduce – not eliminate – major traffic delays.
- Our analysis suggests that for stretches of road at least three lanes wide, the designation of a lane for the exclusive use of self-driving cars will result in more efficient traffic flow during peak traffic hours when self-driving cars account for 5% or more of vehicles on the road. The effectiveness of a designated lane holds so long as total traffic density is below ∼45% which is above average peak traffic density.
- Analysis of our model does not reveal any circumstances under which the introduction of self-driving cars resulted in decreased traffic flow efficiency, so there is no evidence for a need to regulate self-driving cars on that account.
- The impacts of traffic delays are extremely costly across economic, environmental, and quality of life dimensions [2]. The impact of self-driving cars, as a potential boon to traffic flow through greater traffic efficiency but also as a potential threat by potentially increasing total traffic volume [10], must be seriously and actively considered by policy makers.

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