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2017
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Summary Sheet

Analysis of Self-Driving Cars Based on Cellular Automata

Summary

Self-driving, cooperating cars are considered as an efficient solution to improve traffic capacity. In this paper, we analyze the effect of self-driving cars on traffic capacity based on cellular automata traffic flow model with different percentage of self-driving, cooperating cars and different number of lanes.

Firstly we build Traffic Flow Model based on cellular automata. Our Traffic Flow Model comprises two parts, Inflow Model and vehicle following model. In our Inflow Model, we consider that the arrival of vehicles is a random variable. And it can be approximated to obey the Poisson probability distribution. In our vehicle following model, we apply Cellular Automata in describing traffic flow. And we improve the Na-Sch model based on Cellular Automata by changing the definition of random delay probability and adding safety distance, response time into Na-Sch model. We also prove that our model is more accurate and more convincing than the original Na-Sch Model. Then we obtain our vehicle following model: Improved Na-Sch model.

Secondly, we divide traveling vehicles in our model into self-driving cars and manual cars. We think the main difference between self-driving cars and manual cars is that self-driving cars have smaller random delay probability and smaller response time. After adding self-driving cars into our model, we redefine the value of random delay probability and response time. Then the simulation result is different with before. By changing the percentage of self-driving cars, we prove that traffic capacity increases with the increasement of the percentage of self-driving cars.

Finally, we analyze the effect of the cooperation between self-driving cars and the interaction between self-driving cars and manual cars on two-lanes road by adding change lane rule into our traffic flow model. Then, we divide these sections of Interstate 5, 90, 405 and State Route 520 provided by the Excel sheet into two-lanes, three-lanes, four-lanes, and five-lanes. We analyze the effect of self-driving, cooperating cars on different lane individually. Then we prove that traffic capacity increases with the increasement of the percentage of self-driving cars on multiple-lanes. In particular, traffic capacity is best on four-lanes road.

Contents

1 Introduction

1.1 Restatement of the Problem

Traffic capacity is limited in many regions of the United State because of lots of reasons. such as the number of lanes of roads. Sometimes, drivers experience long delays when the volume of traffic exceeds the designed capacity of road networks, expecially on Interstate 5, 90, and 405, as well as State Route 520. Self-driving, cooperating cars are considered as a efficient solution to increase traffic capacity. Self-driving cars is guided by internal computers using internal or possibly external sensors. A cooperating car communicates and exchanges data with other cooperating self-driving cars as it decides what to do.

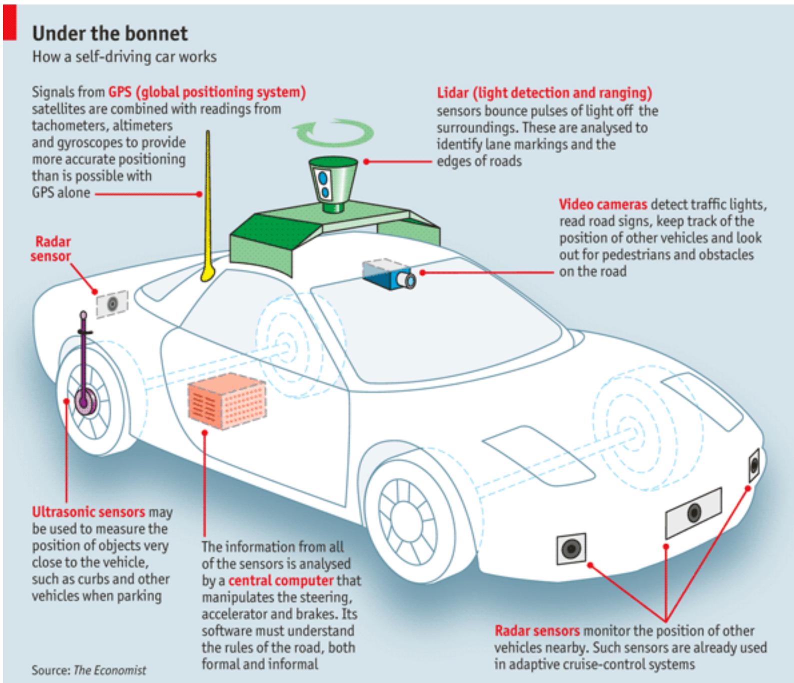

Figure 1: Self-Draving Cars

We are asked to build a model to analyse the effects of allowing self-driving, cooperating cars on the roads that are mentioned before. And how the effects change when the percentage of self-driving cars, the number of lanes and the traffic volume change. We need to analyse is there a equilibrium point and is there a tipping point where performance changes significantly. And we are told to talk about should lanes be dedicated to these cars. We also asked to give other suggestions according to analysis. Meanwhile, our model should consider cooperation between self-driving cars and the interaction between self-driving cars and manual cars.

1.2 Our Work

At first, we build traffic flow model based on cellular automata to simulate real traffic phenomena. our model comprises two parts. In our inflow model, we think that the arrival of vehicles obeys Poisson probability distribution. In improved Na-Sch model, we apply Random Delay Probability, Safety Distance, and Response Time into Na-Sch model. And we proved our model is more accurate than Na-Sch model. Then, we apply self-driving cars into our model. We mainly talk about the effects of the percentage of self driving cars on random delay probability and response time. Then, we conclude the relationship between the percentage of self-driving cars and traffic capacity. Finally, we change the number of lanes in our model to two-lanes, three-lanes, four-lanes, five-lanes individually. We apply real data provided in the Excel sheet into our model. And then we analyze traffic capacity with different number of lanes and different percentage of self-driving cars. We also give some advice to the government according to our analysis.

2 General Assumptions

- The shape and size of vehicles are the same
- Ingore the effcect of toll station at the section of road that we analyze
- The number of traffic lanes in increasing direction and decreasing direction are the same
- Rules in interstate and state route are the same
- The probability of having accidents is very small
- Vehicles wii not stop suddenly in a section of road
- All of the peak traffic time of the day is 2.5 hours

3 Notations and Symbol Description

3.1 Notations

- **milepost:** A marker in the road that measures distance in miles from either the start of the route or a state boundary.
- **average daily traffic:** The average number of cars perr day driving on the road.
- **interstate:** A limited access highway,part of a national system.
- **state route:** A state highway that may or may not be limited access.
- **route ID:** The number of the highway.
- **inncreasing direction:** Northbound for N-S roads,Eastbound for E-W roads.
- **decreasing direction:** Southbound for N-S roads,Westbound for E-W roads.

3.2 Symbol Description

Symbol	Meaning
$P_t(N)$	the probability of N cars arrives during time interval t
$x_n(t)$	the location of vehicle n at time t
$v_n(t)$	the velocity of vehicle n at time t
$d_n(t)$	the distance between vehicle n and $n+1$
v_{max}	the maximum velocity of vehicles
P	random delay probability
ρ_0	initial density of vehicles
F	average traffic flow of vehicles
V	average velocity of vehicles
L	the number of cells for each lane
T	the length of time that vehicles travel
gap_s	the safety distance
T_r	response time of vehicles
α	the percentage of self-driving cars
V_m	average velocity of vehicles in peak traffic hours
SM	startmilepost
EM	endmilepost
ADC	average daily traffic counts
S	length of a section of road
L_a	the numbers of lanes
N1	initial number of vehicles on lanes

4 Traffic Flow Model

Our traffic flow model comprises two parts, inflow model and vehicle following model. In our inflow model, we consider that the arrival of vehicles is a random variable. And it obeys a probability distribution. In our vehicle following model, we apply Cellular Automata in describing traffic flow. And we improve the Na-Sch model based on Cellular Automata by adding some influence parameters into the Na-Sch model. Then we get our vehicle following model: Improved Na-Sch model.

4.1 Inflow Model

A vehicle goes into a section of the road is a random event. Accordingly, the inflow model simulates the stochastic arrivals of vehicles.We assume that the arrival of different vehicles in different time is independent. And for a small enough time interval δt, the probability of the arrival of a vehicle has nothing to do with time t. However the probability is directly proportional to the length of the time intervalδt. After a study about relevant researches and papers, we konw that the total number of vehicles arrived during a time interval can be approximated to obey the Poisson probability distribution. And we have

$$P_t(N) = \frac{\lambda^n}{n!}e^{-\lambda}, n{\geq}0$$

In this formula, n denotes the total number of vehicle arrivals, t denotes the length of time interval, $P_t(N)$ denotes the probability of n. In our model, we let t be one second. λ equals 0.25. Then we can calculate the probability of n cars arrive in one second.

4.2 Improved Na-Sch Model

4.2.1 Na-Sch Model

Cellular automata is an idealized model of physical systems in which both space and time are discrete and physical parameters are limited to a finite number of sets.[1] In recent years, based on cellular automata theory of traffic flow Model is widely used in large-scale traffic flow simulation study. The model divides a section of road into small rectangular cells, and time is divided into small units. This feature simplifies the simulation process significantly. Besides, the state of a cell is controlled by its neighboring cells following a set of rules, which is similar to real traffic phenomena that a cars movement largely depends on its neighboring cars movement. Therefore, it is rational for us to apply Cellular Automata to solve our problem. There are some significant cellular automata traffic models like Na-Sch model proposed by K. Nagel and M. Schreckenberg, FI model proposed by Fukui and Ishibashi.

Na-Sch model is described by K. Nagel and M. Schreckenberg in 1992. The idea behind this model is that the vehicle always tries to travel at maximum speed and does not want a collision. However not every vehicle travels optimally. Na-Sch model is characterized by considering the vehicle speed distribution as normal distribution, while introducing delay rules of random deceleration. The large-capacity, high-speed parallel computation of the model shows the phase transition of the freeway traffic from the moving smooth phase to the local blocking phase.[2] Na-Sch model is composed by four processes, vehicle acceleration process, vehicle deceleration process, random delay process and update of location process.

We assume that the location of vehicle n is $x_n(t)$, the velocity is $v_n(t), v_n(t) \in \{0, 1, 2, \cdots, v_{max}\}$. The vehicles are randomly distributed over a one-dimensional discrete grid of length L, with each cell occupying only a single car at most, $d_n(t)$ donates the distance between vehicle n and vehicle $n+1$, $d_n(t) = x_{n+1}(t) - x_n(t)$. P is the random delay probability of vehicles. The updating rules of the state evolution of the vehicles in Na-Sch model are:

1. **vehicle acceleration process:**

   if $v_n(t){\leq}v_{max}$, the velocity plus one, but is less than the maximum. $v_n(t+1) = min(v_n(t)+1, v_{max})$;

2. **vehicle deceleration process:**

   if $d_n(t){\leq}v_n(t)$, the velocity of the vehicle will equal to $d_n(t)$; otherwise the velocity does not change. $v_n(t+1) = min(v_n(t), d_n(t))$;

3. **random delay process:**

if the velocity of vehicle n is greater than zero, then the velocity will minus one with the probability P; otherwise, it does not change. $v_n(t+1) = max(v_n(t)-1, 0)$ with probability P ;

4. **update of location process:**

   the vehicle moves forward at a new velocity. $x_n(t+1) = x_n(t) + v_n(t+1)$;

The first step reflects the general tendency of the driver to pursue speed, the second step reflects the intention to avoid collision the third step of the randomization includes the driver's different behavior patterns, and the vehicle decelerates with probability P, the fourth step will update the vehicle position. This is the minimized programming set that can reflect real traffic phenomena. Without any rules or changing the order of execution, it can not reflect the real phenomena.

In our simulation, the number of cells for each lane L is 500 and each cell is 7.5 meters in length and 3.5 meters in width. Each cell has two properties, the value of x_n is 0 or 1. When $x_n = 0$, the cell n does not have a car; When $x_n = 1$, there is a car in cell n. In initial state, we set the random delay probability $P = 0.3$ the maximum of velocity $v_{max} = 5m/s$, the length of time interval $T = 60s$, the initial density of vehicles $\rho_0 = 0.01$. We can use the initial density to describe the traffic condition effectively. The smaller the ρ_0 is, the lighter the traffic is; the greater, the heavier.

Then we can calculate average traffic flow of vehicles F, average velocity V, and the density of vehicles ρ to reflect the traffic ability, where

$$\rho = N/L; \qquad V = \frac{1}{T}\sum_{t=0}^{T-1} v(t); \qquad F = \rho V$$

Using these parameters that we set , we can effectively simulate the real traffic phenomena, and use average traffic flow to describe traffic capacity

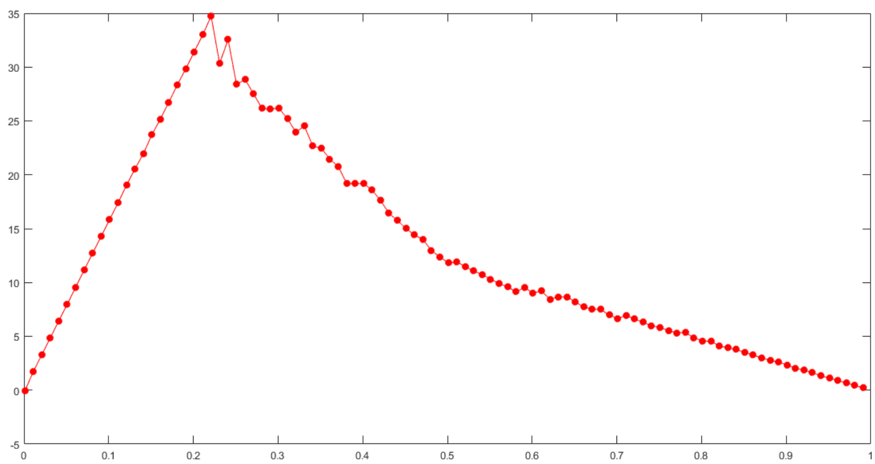

Figure 2: Traffic capacity

According to figure 2, we can conclude that traffic flow increases along with the increasement of the density of vehicles, but after traffic flow reached its maximum point, it decreases along with the increasement of the density of vehicles.

4.2.2 Random Delay Probability

According to the updating rules of the state evolution of the vehicles in Na-Sch model, the value of random delay probability is constant. However, in the real traffic condition, there will be two kinds of situations: When the vehicle moves forward at a large velocity, the preceding vehicle slows down or the expected distance between two cars is not large enough, the driver may delay braking randomly with a large probability. When the preceding vehicle is driving fast or the expected distance between two cars is large enough, The driver may delay braking randomly with a small probability at a slower speed.[3] Therefore, taking into account the random behavior of the driver in the process of travel, we determine the random delay probability P before the updating rules of the state evolution of the vehicles begins, so that the probability is related to the vehicle speed. And then we have

$$P = \frac{1 - e^{-0.1 * v_n(t)}}{1 + e^{-0.1 * v_n(t)}}, \qquad v_n(t) \in \{0, 1, 2, \cdots, v_{max}\}$$

Because our new model takes into account the fact that different vehicle drivers have different behaviors, and connects the random delay probability in the uncertain behaviors with the velocity. So that, the random delay probability of the vehicle in the new model is lower than that of the Na-Sch Model.

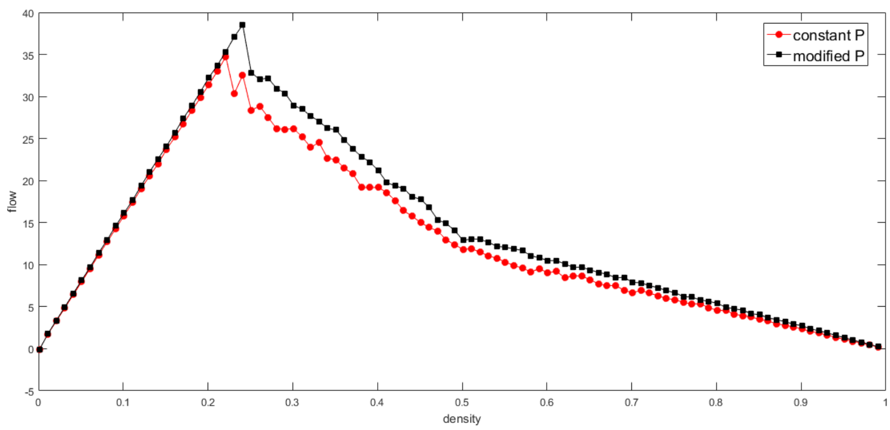

Figure 3: Traffic capacity under modified P

As a result, traffic flow is larger than before under the same density of vehicles after we modified random delay probability. The probability of traffic blockage is less, and the critical density is also slightly larger.

4.2.3 Safety Distance

Na-Sch model does not consider the safety distance gap_s between two vehicle when vehicles are travelling on the road. Safety distance refers to the distance that the vehicle in order to avoid rear-end collision must maintain when the preceding vehicle brakes. We introduced the Gipps safety distance rule into Na-Sch model to impprove the model accuracy and to use the newly established model for in-depth analysis of safe driving behavior in traffic flow.[4] We set the value of safety distance gap_s Then we modify the updating rules of the state evolution of the vehicles in Na-Sch model:

1. **vehicle acceleration process:**

   When the distance between vehicle n and the preceding vehicle is greater than the safety distance, in order to meet the driver's desire for higher speed driving, the vehicle accelerates. $v_n(t+1) = min(v_n(t)+1, v_{max}, d_n(t))$;

2. **uniform speed process**

   When the distance between vehicle n and the preceding vehicle is equal to the safety distance, in the case of ensuring the safety of vehicles, the vehicle does not take any acceleration and deceleration measures. $v_n(t+1) = v_n(t)$

3. **vehicle deceleration process:**

   When the distance between vehicle n and the preceding vehicle is less than the safety distance, the vehicle decelerate. $v_n(t+1) = max(min(v_n(t), d_n(t)))$;

4. **random delay process:**

   if the velocity of vehicle n is greater than zero, then the velocity will minus one with the probability P; otherwise, it does not change. $v_n(t+1) = max(v_n(t)-1, 0)$ with probability P ;

5. **update of location process:**

   the vehicle moves forward at a new velocity. $x_n(t+1) = x_n(t) + v_n(t+1)$;

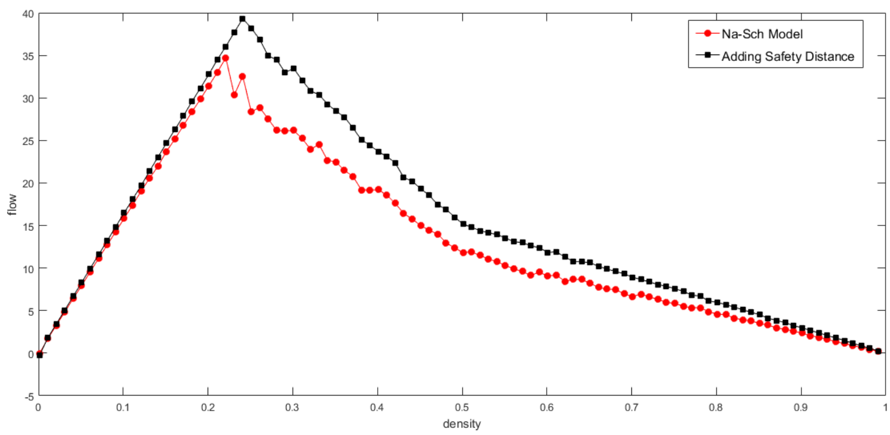

Figure 4: Traffic capacity adding safety distance

After we added safety distance into Na-Sch Model, we can see traffic capacity is better than before, which illustrate this approach can reflect real traffic phenomenon better.

4.2.4 Response Time

In the real traffic condition, we also need to consider response time of vehicles. Response time is the length of time interval from the deriver decides to brake to apply the brake. The less of response time of vehicles, the better of the traffic condition. We apply response time of vehicles into Na-Sch model. Generally, response time for a normal driver is between $0.3s$ to $1s$. In our model, we set response time of vehicles T_r is $0.5s$. And then we add searching velocity of the preceding vehicle process into the updating rules of the state evolution of the vehicles in Na-Sch model as the first process.

- **searching velocity of the preceding vehicle process**

$$v_{n+1}(t+1) = min(v_{max} - 1, v_{n+1}(t), max(0, d_{n+1}(t) - 1))$$

In this model, we can obtain a condition for the vehicle travelling safely.

$$T_r * v_n(t) \leq d_n(t)$$

If any of the following events occurs, there may have an accident between vehicle n to vehicle $n+1$ at the moment $t+1$. These following events can be expressed as mathematical forms.[5]

- $T_r * v_n(t) > d_n(t)$
- $v_{n+1}(t) > 0$
- $v_{n+1}(t+1) = 0$

After applying Random Delay Probability, Safety Distance, and Response Time into Na-Sch model, we obtain our own vehicle following model, as Improved Na-Sch Model. This model considers some real parameters in traffic condition, which makes it more accurate, more convincing.

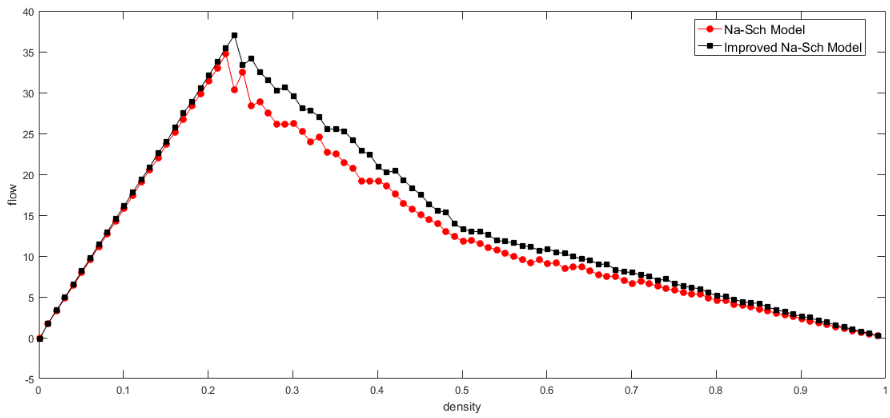

Figure 5: Traffic capacity under diferent models

Then we compare the simulation results of traffic flow based on Improved Na-Sch Model with Na-Sch Model. It indicate that applying safety distance and response time into Na-Sch Model can increase traffic capacity in some ways. As a result, traffic capacity is better and more precise under Improved Na-Sch Model.

5 Self-Driving and Manual-Driving

Self-driving cars also known as unmanned vehicles, are intelligent vehicles that achieve unmanned control through a computer system. self-driving cars rely on artificial intelligence, visual computing, radar, surveillance devices and GPS to work together in a way,so that the computer system can operate a car safely and automatically without any human initiative.

In real traffic condition, self-driving technology can significantly improve road safety. The machine will not fatigue anger, alcohol or distraction, so that it has an unparalleled advantage of human beings.[6]

In our model, we mainly talk about the difference between self-driving cars and manual cars in random delay probability, safety distance, and response time. Self-driving cars are controled by computer system. Then it will decelerate desicively, which means random delay probability in the updating rules of the state evolution of the vehicles in Improved Na-Sch model is small enough. Therefore, we set random delay probability of self-driving cars P_s is 0. Then random delay probability in our model mainly ralys on manual cars. Then we have

$$P^* = (1-\alpha) * \frac{1-e^{-0.1*v_n(t)}}{1+e^{-0.1*v_n(t)}}, \qquad v_n(t) \in \{0, 1, 2, \cdots, v_{max}\}$$

where P^* is random delay probability in our model when self-driving cars are involved, α is the percentage of self-driving cars.

Meanwhile response time of self-driving cars is smaller than response time of manual cars, because self-driving cars are controled by computer system, which will apply brake immediately.[7] In our model, we set response time of self-driving cars T_s is $0.3s$, response time of manual cars T_m is $0.5s$. Then for the expected response time in our model T_{er}, we have

$$T_{er} = \alpha * T_s + (1-\alpha) * T_m$$

In particular, we choose the percentage of self-driving cars as $10\%, 50\%, 90\%, 100\%$ to analyze.

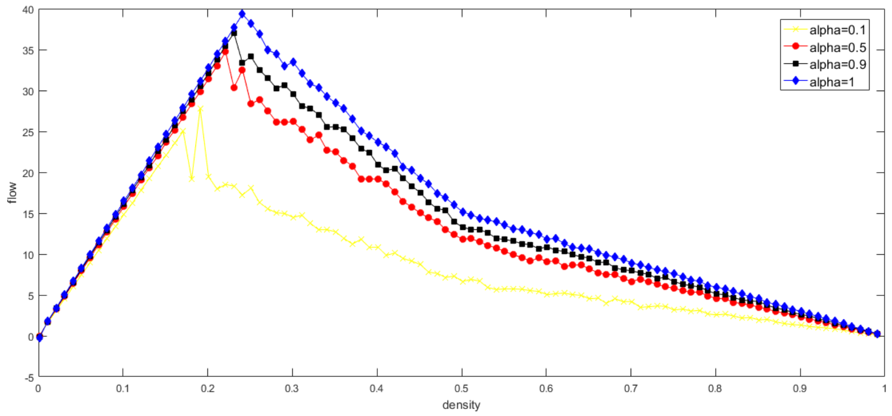

Figure 6: Traffic capacity with different percentage of self-drving cars

After the simulation of traffic flow, we can conclude that traffic capacity is different under different percentage of self-driving cars. When the percentage of self-driving cars are $10\%, 50\%, 90\%, 100\%$, the greater the percentage of self-driving cars is, the better traffic capacity is.

After a further analysis of traffic capacity under different percentage of self-driving cars, we obtain average flow at a section of road under every percentage of self-driving cars from 1% to 100%.

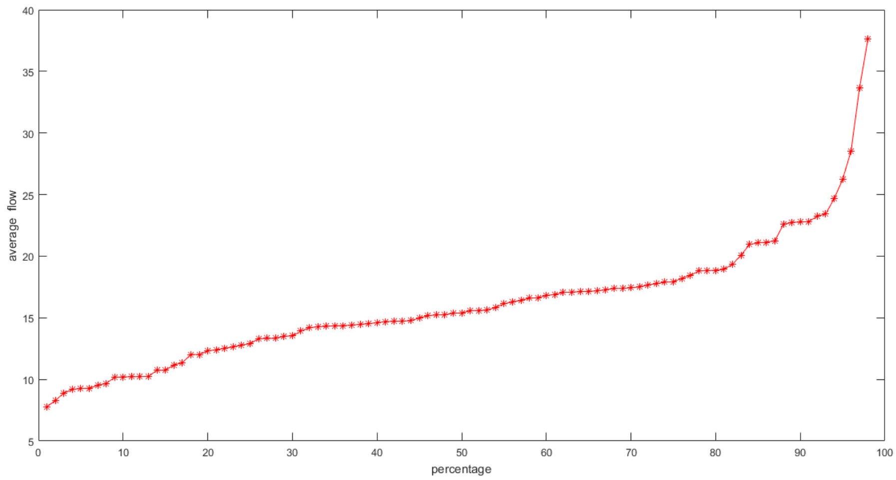

Figure 7: Traffic capacity with different percentage of self-drving cars

Traffic capacity is positively correlative with the percentage of self-driving cars. When the percentage of self-driving cars increases, traffic capacity increases. And traffic capacity reaches its maximum when the percentage of self-driving cars is 100%.

6 Real Data Analysis

These traffic conditions that we disscused in our model are based on single lane. But most of highways have more than one lane in real phenomena. We change the number of lanes in our model to two-lanes, three-lanes, four-lanes, five-lanes individually. Because of the cooperation between self-driving cars as well as the interaction between self-driving cars and manual cars, self-driving cars can get the state of other vehicles around it. According to the state of other vehicles, self-driving cars may change lane with a given probability.[8] After some analysis, we add the rule of change lane into the updating rules of the state evolution of the vehicles in Improved Na-Sch model.

When $v_n(t) \geq d_n(t)$, the vehicle is considered to change lane or decelerate. If the lane beside the proceding vehicle has enough space, the vehicle will change lane with probability P_t, otherwise, it will decelerate to $max(d_n(t) - 1, 0)$ with probability P_d or decelarate to $d_n(t)$.

The cooperation between self-driving cars and the interaction between self-driving cars and manual cars can provide lots of information to vehicles about surrounding cars.[9] Self-driving cars can move forward safely according to these information. As a result, it will improve traffic capacity sightly.

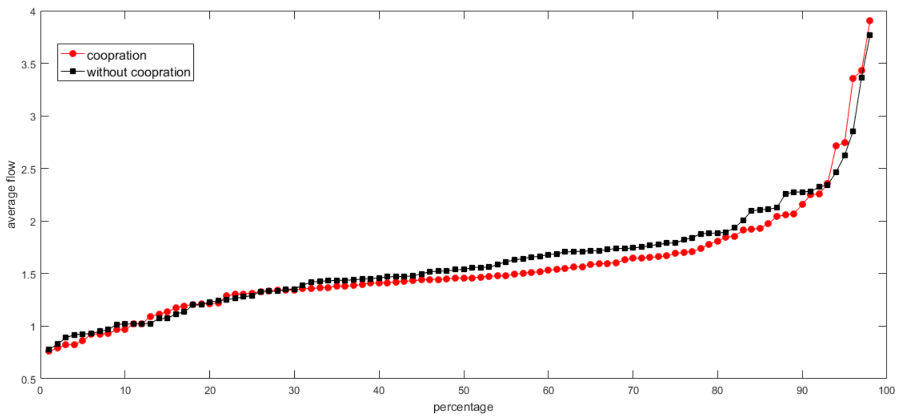

Figure 8: Traffic capacity with cooperation between cars

Then,We divide the data provided by Excel sheet into four categories according to the number of lanes at each section of road. $L_a(i)$ denotes the number of lanes that the ith part has, where $L_a(i)$ can equals 2, 3, 4 or 5 in the ith part of highway. $SM(i)$ denotes StartMailpost , $EM(i)$ denotes EndMailpost. S(i) donates the length of the ith part of highway. We assume that mean speed of vehicles on the ith part of highway V_m is 30 miles per hour during peak traffic time. Then, T_m denotes time for a car to go through the ith part of highway, and $T_m = \frac{S(i)}{V_m}$. ADC(i) denotes Average daily traffic counts of the ith part. Then the initial number of cars driving in either direction of the ith part is N_i. And $N_(i) = \frac{ADC(i)*8\%*T_m}{2.5}$ We also define the length of each cell in our model L is 5 meters and the length of time interval of one step T is one second. And the maximum velocity that given by data is 60 miles per hour.

After we redefined the values of the parameters according to the supplied data in our model, we can get these simulation result for two-lanes model three-lanes model four-lanes model and five-lanes model individually.

6.1 Two-Lanes

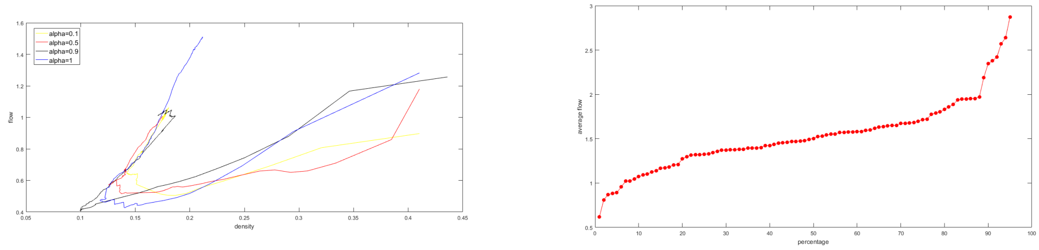

Figure 9: traffic capacity with different percentage of self-driving cars(two-lanes)

When we apply self-driving cars into our two-lanes model, traffic capacity increases as the increasement of the percentage of self-driving cars. Especially when the percentage is between 80% to 100%, traffic capacity increases markedly. And there is not a equilibria point of the relationship between the percentage of self-driving cars with average flow.[10] When density of vehicles is large, traffic cappacity increases significantly; when density of vehicles is small, traffic capacity barely increases with $10\%, 50\%, 90\%$ self-driving cars involved.

6.2 Three-Lanes

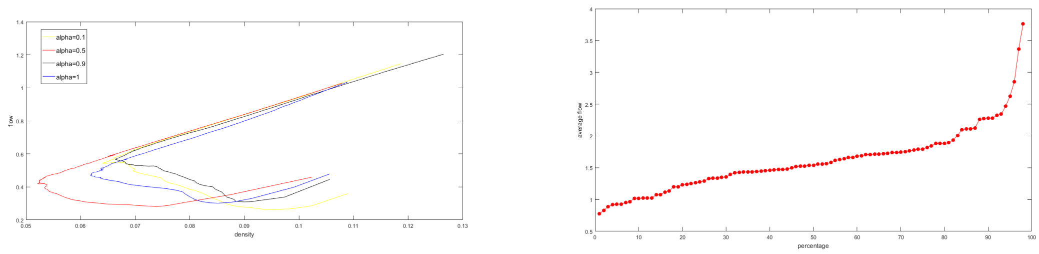

Figure 10: traffic capacity with different percentage of self-driving cars(three-lanes)

When we apply self-driving cars into our three-lanes model, traffic capacity increases as the increasement of the percentage of self-driving cars. Especially when the percentage is between 90% to 100%, traffic capacity increases markedly. And there is not a equilibria point of the relationship between the percentage of self-driving cars with average flow.[11] When density of vehicles is small, traffic cappacity increases significantly; when density of vehicles is large, traffic capacity barely increases with $10\%, 50\%, 90\%$ self-driving cars involved.

6.3 Four-Lanes

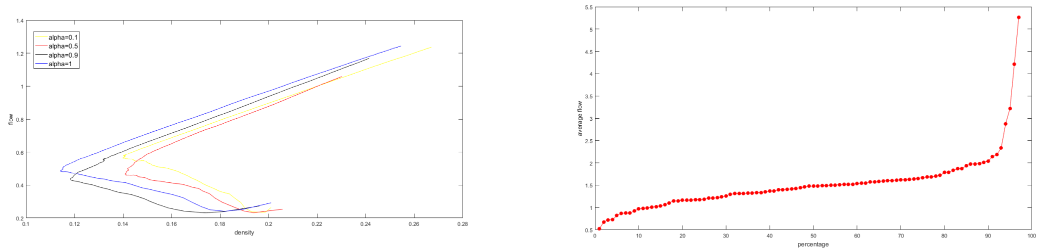

Figure 11: traffic capacity with different percentage of self-driving cars(four-lanes)

When we apply self-driving cars into our four-lanes model, traffic capacity increases as the increasement of the percentage of self-driving cars. Especially when the percentage is between 90% to 100%, traffic capacity increases markedly. And there is not a equilibria point of the relationship between the percentage of self-driving cars with average flow. Traffic capacity increases sightly at any value of density of vehicles with $10\%, 50\%, 90\%$ self-driving cars involved.

6.4 Five-Lanes

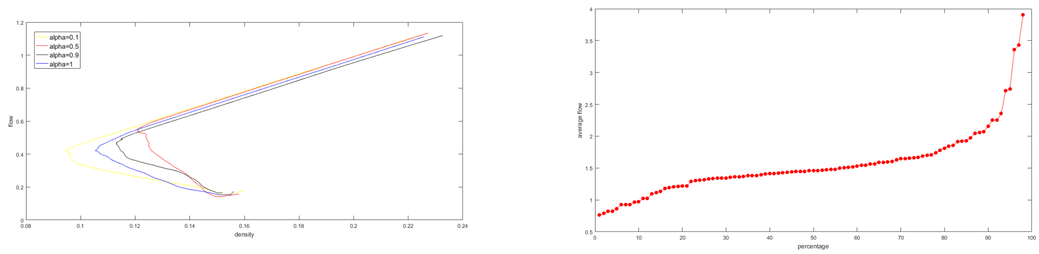

Figure 12: traffic capacity with different percentage of self-driving cars(five-lanes)

When we apply self-driving cars into our five-lanes model, traffic capacity increases as the increasement of the percentage of self-driving cars. Especially when the percentage is between 90% to 100%, traffic capacity increases markedly. And there is not a equilibria point of the relationship between the percentage of self-driving cars with average flow. When density of vehicles is small, traffic cappacity increases significantly; when density of vehicles is large, traffic capacity barely increases with $10\%, 50\%, 90\%$ self-driving cars involved.

7 Sensitivity Analysis

In Improved Na-Sch Model, we set the maximum velocity V_{max} is $5m/s$, and λ in inflow model is 0.25. But, for different value of these two parameters, traffic capacity may have slight changes. We choose the maximum velocity V_{max} as $5m/s, 10m/s, 15m/s$, and hold other parameters constant.

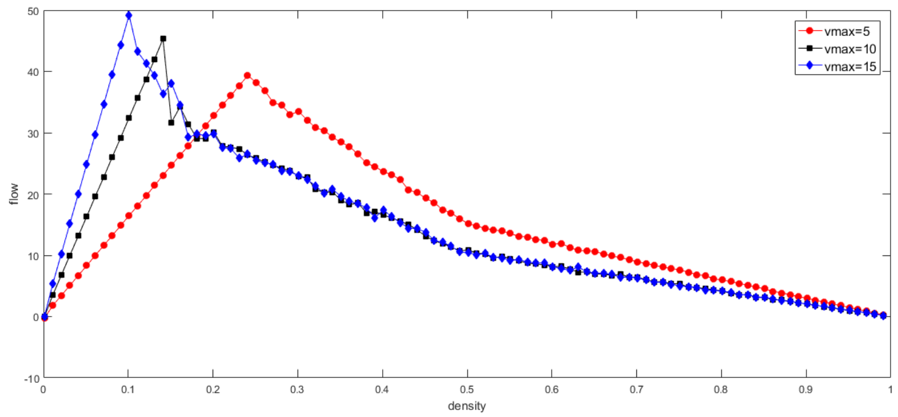

Figure 13: Traffic capacity with different maximum velocity

When density of vehicles is small, traffic capacity will increase sightly as the increment of maximum velocity; when density of vehicles is large, the maximum velocity does not have much influence on traffic capacity.

To analyze the effect of λ on traffic capacity, we choose λ as $0.25, 0.3, 0.35$, and hold other parameter constant.

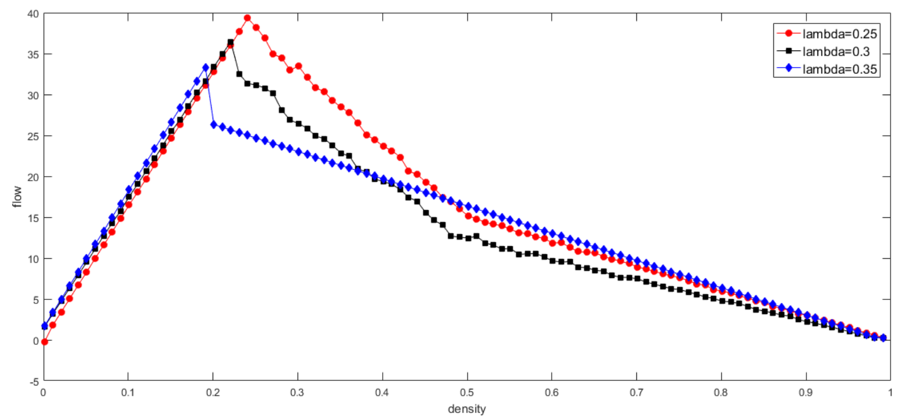

Figure 14: Traffic capacity with different λ

Then traffic capacity does not change too much with the increasement of λ when density of vehicles is small; when density of vehicles increases traffic capacity will decrease with the increasement of λ.

8 Conclusion

According to our analysis, self-driving, cooperating cars is an efficient solution to solve traffic congestion problems. It will improve traffic capacity markedly. And traffic capacity increases with the increasement of the percentage of self-driving cars. The greater the percentage of self-driving cars is, the better traffic capacity is.Meanwhile, the cooperation between self-driving cars and the interaction between self-driving cars and manual cars will improve traffic capacity in some ways.

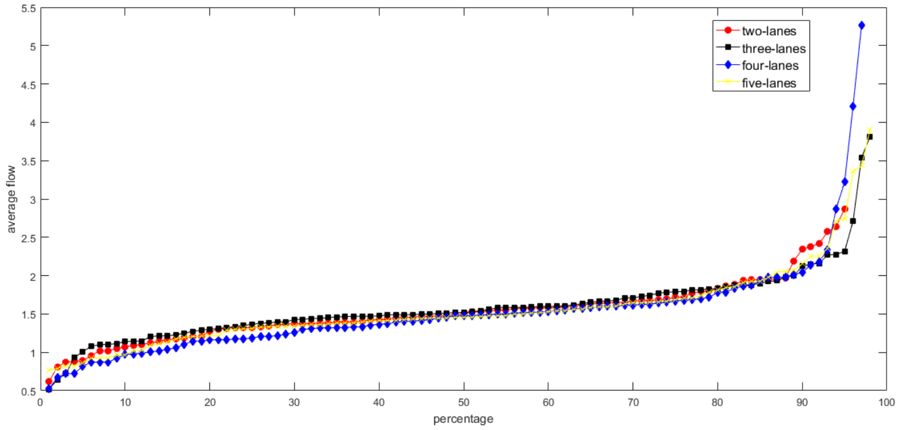

Figure 15: Traffic capacity on multiple-lanes road

It is also correct when vehicles travel on two-lanes road, three-lanes road, four-lanes road, and five-lanes road. According to figure 15, we can conclude that traffic capacity increases when the percentage of self-driving cars increases on any multiple-lanes road. And traffic capacity is best when vehicles travel on four-lanes road.

9 Strengths and Weaknesses

9.1 Strengths

- We use cellular automata to simulate traffic flow, so that the result is reliable.
- We consider the probability of having accident in our code.
- We add safety distance and response time into Na-Sch model, so that the simulation result is more real.
- We apply these data provided in Excel sheet into our model effectively, and prove our model is convincing under real traffic condition.

9.2 Weaknesses

- The effect of self-driving cars on traffic flow that we talk about is not comprehensive.
- Did not apply all the background knowledge into our model

Letter to the Governor

Dear Governor

We are students who are participating in the American College Students Mathematical Contest in Modeling. We chose problem B and did some analysis about the effect of self-driving cars on traffic capacity. As we all know, traffic capacity is limited in many regions because of many reasons. And drivers will experience long delays during peak traffic hours if the volume of traffic exceeds the designed capacity of the road networks. And self-driving, cooperating cars are considered as a efficient solution for the traffic congestion because of its convenience and safety.

We analyzed the effect of self-driving cars on traffic capacity. And we use Interstate 5,90,405 as the subjects. We concluded that when the percentage of self-driving cars increases, traffic capacity increases continuously. The greater the percentage of self-driving cars is, the better traffic capacity is. Traffic capacity increases slowly when the percentage increases from 10% to 50% to 90%. Traffic capacity increases markedly when the percentage increases from 90% to 100%. And there is no equilibrium point. Meanwhile, the cooperation between self-driving cars and the interaction between self-driving cars and manual cars will improve traffic capacity in some ways. It is also correct on multiple-lanes road. Especially, when vehicles travel on four-lanes road, traffic capacity is best.

We think the government should put more resources to improve self-driving technology, and put more self-driving, cooperating cars into use on the road. So that traffic capacity will improve significantly. And you should put most of self-driving, cooperating cars on four-lanes road, because the influence on four-lanes road is higher compared with the influence on other multiple-lanes road. You can build a self-driving cars management platform in order to enhance the cooperation between self-driving cars and manage self-driving cars handily. And it is an efficient way to improve the traffic capacity by expanding the traffic volume to a certain level and converting it into a freeway or sub-lane highway. It is also useful to improve traffic capacity by strengthening traffic management and improving a variety of traffic management facilities. With these methods, traffic capacity will improve significantly.

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