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Reduce Greenhouse Gas Emissions through Ramp Meter Control

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***Abstract*—The emission of greenhouse gases varies non-linearly with vehicle's speed and acceleration, which indicates a possibility to optimize it through mobility control on urban corridors. A 1.5-mile 4-lane highway section with one on-ramp meter was modeled and simulated at various scenarios by adjusting red-time interval of the meter. It is observed that in light or moderate traffic senarios, the optimal red time interval increases with traffic density. However, when traffic becomes very heavy or jammed, the optimal red time actually decreases. Our simulation also shows the overall emission decreases with highway speed limit. The fact that the red time interval needs to be reduced under heavy traffic in order to reduce CO_2 emission indicates a trade-off between improving highway throughput and reducing CO_2 emission. Optimization plans solely targeting for higher throughput not necessarily leads to lower emission, on the contrary, it may increase the emission in some cases.**

Keywords—Traffic modeling, highway mobility, emission optimization

I. INTRODUCTION

While "global warming" gradually turns into a fact rather than a hypothesis, people are more and more concerned about the greenhouse emissions generated from both civil and industrial sources. President Obama pledged at the United Nations conference in Copenhagen to reduce American greenhouse emissions by 17 percent by 2020 compared with 2005 level. This has stimulated many activities in both city- and state-levels aiming at reducing greenhouse gas emission from a variety of sources.

Although electricity generation, industrial wastes, neighborhood activities (dry cleaners, lawn mowers etc) and farming all contribute to the greenhouse emissions in southern California, automobile emission remains to be the most challenging problem due to the rapidly increasing populations and expanding urban areas during recent decades. This stems from the use of gasoline for power. The burning of cheap, ordinary gasoline gives off not only pollutants (hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NO)) [1], but also carbon dioxide (CO_2) which is considered the major factor for global warming. These products contribute greatly to smog, ozone, cancer, lung disease, illness, and the greenhouse effect. A gallon of gasoline is assumed to produce 8.8 kilograms (or 19.4 pounds) of CO_2 [2]. In cities such as Los Angeles, California, the problem is extremely apparent due to the large population of automobile vehicles.

While replacing existing gasoline based vehicles with those using clean energies is the ultimate solution, it is rather a long term process. Therefore, the first solution in mind may be to reduce the number of vehicles on road by providing public transportation etc. However, due to highly distributed neighborhoods and business areas, the public transportation can satisfy only a very limited percentage of residence, therefore reducing number of vehicles on road has limited success in southern California areas. Nevertheless, there is another option we may chose: reduce the greenhouse gas emission through intelligent operation control on urban corridors, including highways and major local roads. It has been reported that the rate of greenhouse emission from running vehicles highly correlates with their speed as well as acceleration [3,4]. Moreover, the emission rate is also tightly correlates to the vehicle type, for example, heavy trucks emit 4 times more than passenger cars on average [4-6]. The difference may enlarge during stop-and-go conditions as heavy vehicles need more propulsion to accelerate. An intuitive learning from these facts is that if all vehicles are moving smoothly (without frequent accelerations and brakes) at a moderate speed, the overall emission will be minimized. This can be achieved by implementing a variety of intelligent operation strategies, such as adaptive ramp meter control.

California is one of very few states that started intelligent transportation systems' (ITS) implementation in 70's. Nowadays, California already has relatively matured ITS infrastructures, including Freeway management systems, Incident management systems, Arterial management systems etc. California also took lead in the development of a performance measurement system (PeMS) that will serve transportation professional and decision makers to actively control the mobility on corridors based on real-time road conditions. Adaptive ramp meter is just one example of these intelligent operations strategies.

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Current studies on adaptive roadway controls aims mostly on improving traffic efficiency or highway mobility [8-12]. Controller design methods vary from artificial neuron networks [8-9], model predictive control [10-11, 13] to fuzzy logic [12]. Few of them take greenhouse emissions into consideration. A recent work of Zegeye [13] considers optimizing pollutant emissions on roadways through active speed limit control. Although the road model they considered in this work is a simple straight road without ramp and local roads, they illustrate that a traffic control strategy aiming solely at reduction of total time spent does not necessarily reduce the level of emission. B. Park et. al [16] compared the average fuel consumption between strategies aiming to reducing queuing time and strategies aiming to minimize fuel consumption on local arterials. They also concluded that strategies aiming to reduce queuing time not necessarily reduce emission. So a specific controller aiming at reducing emission is necessary. This study contributes to the field by considering a comprehensive highway model with on/off ramps and an adjustable ramp meter. The roadway control is achieved by ramp meter control, which is more practical now compared with active speed control. Our goal is to monitor the effect of ramp meter control on total greenhouse emission, therefore, suggest a feasible road control strategy in terms of minimizing the greenhouse emission.

II. DATA COLLECTION

Collecting real world traffic data, such as incoming traffic flows, class of vehicles and percentage, speed of movement, traveling time in construction zone, is necessary to build a model that produces reliable results. In this project, two types of data are needed, vehicle greenhouse gas emission data and the real world traffic data.

A. *Vehicle Emission Data*

The CO_2 emission data were collected through internet resources. Nowadays, all vehicles on market are required to be accompanied by a parameter called global warming score. Therefore, the CO_2 emission of each type of vehicle could be found from a variety of websites [4-6]. This eases our data collection significantly. To further simplify our model, we categorized the vehicles into 6 categories, i.e. Cars, SUVs, Hybrid vehicles, Light-duty trucks, Buses and Cargo Trucks. The collected emission data for each type of vehicle are then scaled to speed dependent profile according to [15]. Fig.1 shows emission vs. speed plot for passenger cars. This result is an average of 11 different models of gasoline passenger cars, including Honda, Toyota, Audi and many more. SUVs, Pick-up trucks, Hybrid vehicles, Cargo trucks and Buses all show a similar trend of variation as a function of speed.

In addition to speed, acceleration is another factor affecting CO_2 emission. Speed variation is expected frequently on urban corridors, especially in crowded LA area. Therefore, consideration of instantaneous acceleration will improve the validity of our model. Panis et al. has developed a model of CO_2 emission as a function of acceleration [14]. Their model is scaled and combined with our velocity data for our CO_2 emission calculation, which will be explained later in this article.

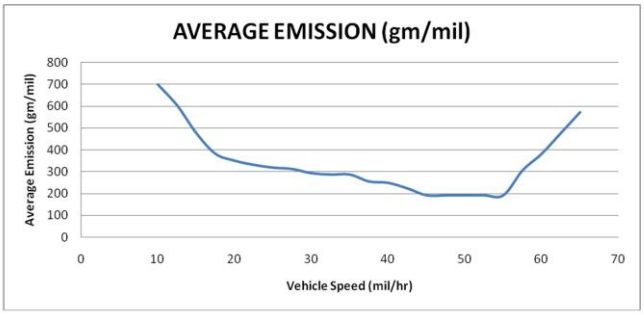

Fig. 1 Passenger Car CO_2 emission rate (grams/mile) as a function of speed [4-6].

B. *Traffic Data*

Collecting real world traffic data, such as incoming traffic flows, class of vehicles and percentage, is necessary to build a microscopic traffic model that produces reliable results. For this part of data collection, we used video monitoring method. We placed digital camcorder on interested roadway sections at selected time slots of a day. We took video recording of I-710 south bound at 9:00am, 12:00pm, 4:00 pm and 7:00pm. Each video recording was about 20 minutes long. The vehicle counts and vehicle type are then documented. The data are collected at 4 different locations: before the on ramp, on the on-ramp, on the off ramp and after the off-ramp. The raw data is then formatted into Origin-Destination matrix as shown in Table 1. Fig. 2 below shows a snapshot of our raw video recordings.

Fig. 2 Video snapshot on I-710 southbound.

III. MODEL DEVELOPEMENT

In this study we modeled a 1.5 mile long, 4-lane highway section, single direction, with an on-ramp and an off-ramp using PARAMICS software.

A. *Paramics Software*

PARAMICS software (by QUADSTONE) is a microscopic traffic simulation package, which supplies modeling ability to simulate complicated road networks and monitor individual section of highways . In PARAMICS, the instantaneous traffic data, such as traffic flow, instantaneous velocity and instantaneous acceleration, are collected by placing loop detectors on interested locations. The collected data are in .cvs format as a function of time. This eases the total emission calculation as the total emission rate is not only changing with velocity, but also the acceleration. Moreover, the emission needs to be monitored at each time point and summed to reach the total emission. So, a velocity and acceleration data at individual time point is necessary.

In PARAMICS, the traffic flow is controlled by Origin-Destination Matrix (OD Matrix), i.e. the number of vehicles moving from a certain Origin to a certain Destination. The OD matrix is derived from the collected traffic data. Placing a Ramp meter signal is also convenient in PARAMICS. The signal profile, i.e. red interval and green interval, can be easily adjusted to monitor different control strategies.

B. Traffic Model Configuration

Fig. 3 shows a configuration of the road section to be modeled. Detectors are placed on main highway only. Each lane is monitored by its individual detectors.

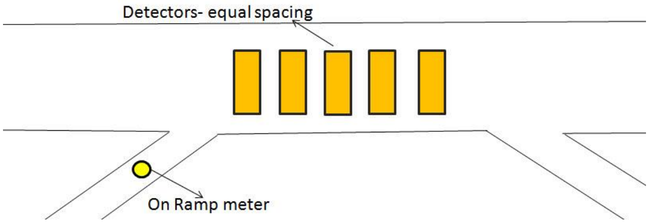

Fig. 3 Road configuration of a 4 lanes highway section with one on ramp and one off ramp.

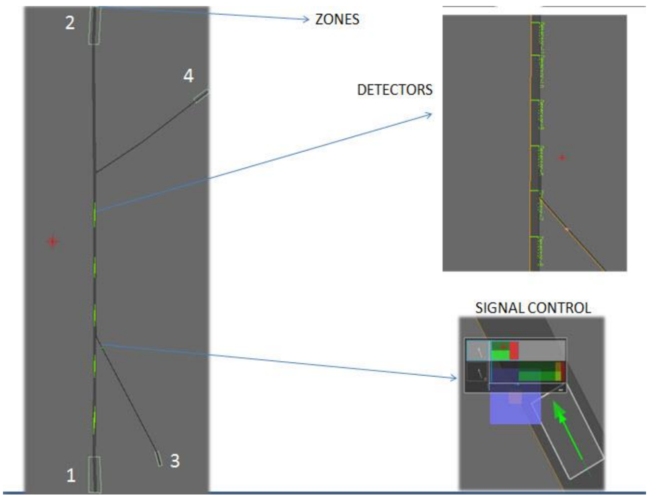

Fig. 4 Screen shot of PARAMICS model.

Fig. 4 shows a screen shot of our PARAMICS model. The left hand side panel is the complete view of the road model. Zone 1 is the incoming origin of highway, zone 2 is the destination of highway, zone 3 is the origin of on-ramp, zone 4 is the destination of off-ramp. The OD matrix controls the number of vehicles traveling between zones. The top right panel is the blow-up of detectors. It can be seen that the detectors are equally spaced. The bottom right panel is the blow-up of ramp meter signal. The signal in PARAMICS could be either a 3 phase signal (green-yellow-red) or a two phase only (green-red). In this study, since we are modeling a ramp meter, a two phase signal profile is used with fixed green time interval.

Table 1 *Origin-Destination Matrix for 6 types of vehicles for 40000 vehicle/hour simulation*

Cars				
Zone	1	2	3	4
1	0	15452	0	900
2	0	0	0	0
3	0	1000	0	0
4	0	0	0	0

Hybrid				
Zone	1	2	3	4
1	0	3784	0	208
2	0	0	0	0
3	0	192	0	0
4	0	0	0	0

SUV				
Zone	1	2	3	4
1	0	8652	0	444
2	0	0	0	0
3	0	504	0	0
4	0	0	0	0

Pickup				
Zone	1	2	3	4
1	0	3728	0	176
2	0	0	0	0
3	0	156	0	0
4	0	0	0	0

Cargo				
Zone	1	2	3	4
1	0	4256	0	160
2	0	0	0	0
3	0	256	0	0
4	0	0	0	0

Bus				
Zone	1	2	3	4
1	0	132	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

Table 1 displays the OD matrix used for a typical traffic density, 40000 vehicles per hour. In our model, six types of vehicles are considered, i.e. Cars, Hybrid vehicles, SUVs, Light-duty trucks, Buses and Cargo trucks. A specific OD matrix is used for each of them.

The matrix displays the number of vehicle traveling from a specific original zone to a specific destination zone. The vertically numbered zones are origins and the horizontally numbered zones are destinations.

The model calibration was done by tuning the global simulation parameters with the goal to minimize the vehicle count difference at specific locations between simulation and video recording. The parameters being adjusted include: queue gap distance, queuing speed and mean driver reaction time. After calibration, the queue gap distance is set at 8.00 ft; queuing speed is set at 9.00 mph; and mean driver reaction time is set at 0.45 s. The default values for those parameters are 32.81 ft, 4.47 mph and 1.00 s, respectively. The huge difference between default and calibrated value indicates the necessity for calibration.

C. Emission Model

The total CO_2 emission is then calculated using the following formula.

$$Emission = \left(\sum_{i=1}^{n}\sum_{j=1}^{6} N_j \times Y_j \times 0.06214\right) Grams$$

Where,
i = i^{th} section of the freeway (The freeway is divided in to 'n' sections, each of 100m length, i.e. 0.06214 mile)
j = j^{th} vehicle type
N_j = Number of vehicles of type 'j' (on the freeway section i)
Y_j = Emission from the vehicle of j^{th} type

j=1: REGULAR CARS

Y_1=Max [0, A_1 + A_2Vn(t) + A_3Vn(t)^2 + A_4An(t) + A_5An(t)^2 + A_6An(t).Vn(t)]

j=2: HYBRID CARS

Y_2= Max [0, B_1 + B_2Vn(t) + B_3Vn(t)^2 + B_4An(t) + B_5An(t)^2 + B_6An(t).Vn(t)]

j=3: SUVS

Y_3= Max [0, C_1 + C_2Vn(t) + C_3Vn(t)^2 + C_4An(t) + C_5An(t)^2 + C_6An(t).Vn(t)]

j=4: PICKUP TRUCKS

Y_4= Max [0, D_1 + D_2Vn(t) + D_3Vn(t)^2 + D_4An(t) + D_5An(t)^2 + D_6An(t).Vn(t)]

j=5: BUSES

Y_5= Max[0, E_1 +E_2Vn(t) +E_3Vn(t)^2 + E_4An(t) + E_5An(t)^2 + E_6An(t).Vn(t)]

j=6: CARGO TRUCKS

Y_6= Max[0, F_1 + F_2Vn(t) + F_3Vn(t)^2 + F_4An(t) + F_5An(t)^2 + F_6An(t).Vn(t)]

, where Vn(t) represents Instantaneous Speed (mile/hr); An(t) represents Instantaneous Acceleration (ft/s^2).

Table 2 Model Coefficient for 6 types of vehicles.

i =	1	2	3	4	5	6
A_i	887.22	-34.979	0.4304	4.87	2.86	2.08
B_i	522.4	-20.596	0.2535	4.09	2.99	1.27
C_i	928.15	-36.593	0.4503	5.09	2.99	2.18
D_i	1061.6	-41.854	0.5151	5.82	3.42	2.49
E_i	3342.6	-131.78	1.6217	23.29	13.68	9.97
F_i	4240.3	-167.18	2.0572	23.28	13.72	9.93

In Fig. 5, we plot the modeled vehicle emission as a function of velocity only (set acceleration to zero). In Fig. 6, we present the CO_2 emission as a function acceleration only (set velocity to 65mph).

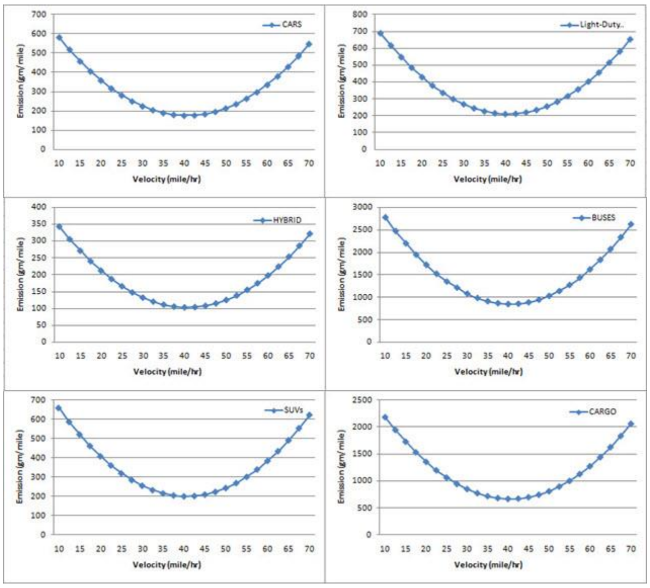

Fig. 5 Modeled Emission vs Velocity plots.

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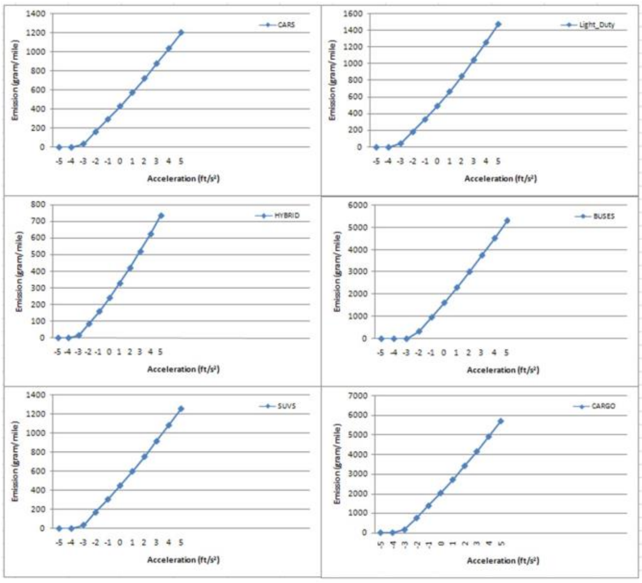

Fig. 6 Emission vs Acceleration plot with velocity fixed at 65mph.

IV. RESULTS AND DISCUSSIONS

A. Effect of Red Time Interval

To study the effect of ramp meter's red time interval, we first simulated a light traffic scenario, i.e. 20000 vehicles/hour. The speed limit is set to 65 mph, which is the current speed limit on I-710. The ramp meter's red time interval is then tuned to 0s, 5s, 10s, 15s, and 20s, respectively, and the point data are collected.

Each loop detector in the network will generate 4 point data files, one for each lane. At each detector location, a vehicle specific emission rate is calculated by applying the vehicle specific formula described earlier. It is assumed that the vehicle maintains the same emission rate until it reaches the next detector, where the emission rate is calculated again. The emission rate is then multiplied by the distance between detectors (0.06214 mile in our case) and divided by total vehicle counts to give average emission per vehicle. Table 3 gives a snapshot of a cleaned point data file after sorted by vehicle types. The program is set to collect point data every 2 seconds and the simulation time is set to 2 hours. CO_2 emission is then calculated for each ramp meter timing scenario and the result is plotted in Fig. 7.

Under light traffic senario, the average emission drops to a minimum if the red time interval of ramp meter is set to 5s. This indicates it is feasible to minimize the emission on highway by adjusting ramp meter timing. Further prolonging the red time interval results in increased average emission. This probably because all vehicles are moving relatively smoothly in light traffic situation, therefore, the average speed becomes the dominant factor for overall emission. As we increase the red time interval, less vehicles get onto main freeway. This results in higher average speed since most of the drivers tends to drive at or beyond the speed limit (65mph). From the emission profile presented in Fig 1, one can observe the vehicle emission is larger than average at 65 mph. Therefore, the emission shows an increasing trend as we increase the red time interval. This result suggests the ramp meter timing should be adjusted to shorter red time interval during light traffic in order to minimized the average emission.

Table 3 Snapshot of cleaned simulation data for 20000 vehicle/hour, red time interval=0s.

Time	Type	ID	Flow	Headway	Gap	Speed	Acc
170.1	23	17	1475	2.441	2.18	70.71	-0.001
177.1	23	46	510	7.054	6.864	69.21	-0.011
180.7	23	28	1359	2.65	1.941	69.91	-0.025
184	23	26	1094	3.291	3.098	66.44	0
186.1	23	25	3121	1.153	0.917	66.64	0.596
191.8	23	49	3428	1.05	0.772	64.35	0
194.7	23	27	3626	0.993	0.749	64.67	1.071
195.8	23	60	3418	1.053	0.845	65.07	1.833
198.8	23	47	3631	0.991	0.751	65.15	-0.004
199.9	23	80	3431	1.049	0.843	65.15	-0.007
200.5	23	56	6053	0.595	0.389	65.07	-0.016

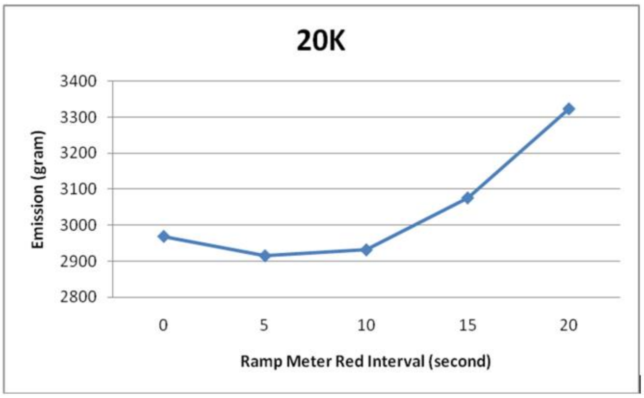

Fig. 7 Emission vs. Red time interval of ramp meter for 20000 vehicle/hour scenario.

B. Effect of Traffic Density

We then ran the simulation for a variety of traffic density using scales distribution of vehicle types. The results are summarized in Fig. 8.

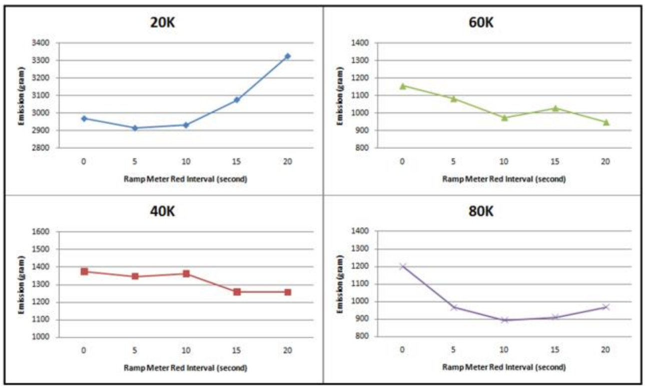

Fig. 8 Emission vs. Ramp meter red time for different traffic density.

Let's first focus on the optimal red time interval. It can be observed that ramp meter red time interval have an impact on vehicle emission for all traffic density. However, the optimal red time interval varies significantly among different traffic densities. For example, the optimal red time interval for 20000 vehicle/hour senario is 5 seconds, but it is 15 seconds for 40000 vehile/hour senario; 20 seconds for 60000 vehicle/hour senario and 10 seonds for 80000 vehicles/hour senario. To further discuss the impact of traffic density on optimal red time interval, we plot the optimal red time interval vs. traffic density in Fig. 9.

A typical jam-free traffic density is considered to be 50-60 vehicles per mile per lane. On the other hand, 200-250 vehicles per mile per lane can be considered jam. In our model, we are considering a 4 lane highway with a speed limit of 65mph. After a simple conversion, 13000 to 15600 vehicle per hour can be considered light (or jam-free) traffic; and 52000 to 65000 vehicle per hour can be considered jam. In our simulations, 20000 vehicle/hour senario could be considered as light traffic, 40000 vehicle/hour and 60000 vehicle/hour senarios could be considered as moderate traffic, and 80000 vehicle/hour senario is considered heavy (jammed) traffic.

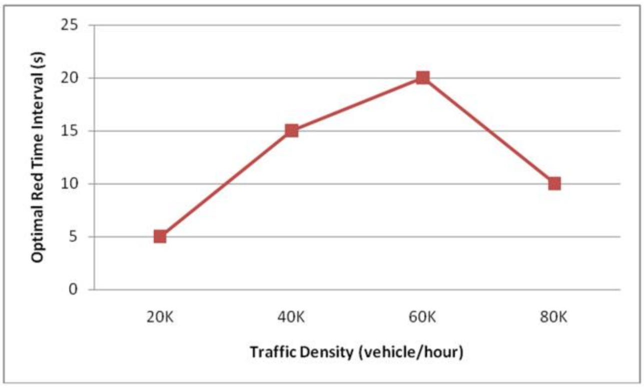

Fig. 9 Optimal Red time interval v. Traffic density. Speed limit is 65mph; green time interval is fixed at 5 seconds.

From Fig. 9, we can see that in light or moderate traffic senarios, the optimal red time interval increases with traffic density. However, when the traffic becomes very heavy or jammed, the optimal red time actually decreases. In light traffic, as we mentioned in previous section, the speed is the dominant factor for average emission because there are very few stop-and-go situations. Over-adjust the red time interval results in higher average speed on main lanes, therefore, higher emission. In moderate traffic, it is observed that the overall trend of emission reduces with increase of red time interval. This is because the vehicle's movement is no longer as smooth as in light traffic situation. Some stop-and-go can be observed during our simulation. Therefore, increasing red-time interval could ease this situation by allowing few vehicle get onto the main lanes. However, when traffic is already jammed on main lanes, i.e. the heavy traffic senario. Limiting the number of vehicles getting into the freeway could not effectively reduce the number of stop-and-gos. On the other hand, it may give chances for drivers to do more frequent accelarations, as they see more spaces in front of them. Therefore, prolonging the red-time interval beyond threshold will increase the emission.

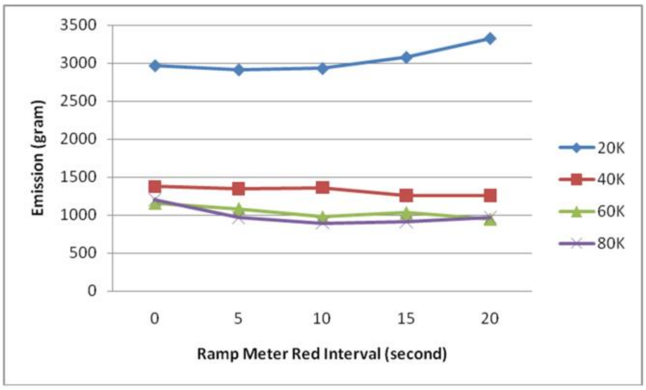

Fig. 10 Emission vs. Ramp meter red time interval for 20K/hr, 40K/hr, 60K/hr and 80K/hr.

In Fig. 10, we combine the emission data of all traffic density scenarios into one plot. As the traffic density increases, the average emission decreases. This indicates that the average speed dominates CO_2 emission more than the acceleration does. In heavier traffic, the overall speed of the vehicles is reduced, which explains the reduction in emission.

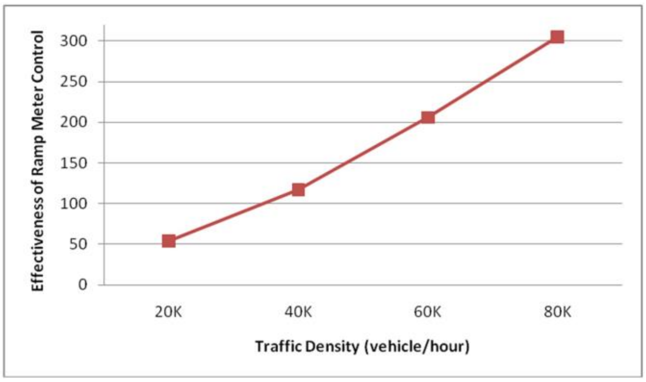

Fig. 11 Effectiveness of ramp meter control vs. Traffic density. Effective is calculated using the ambient emission minus the optimized emission in gram.

Another question we may ask here is: how effective is the ramp meter control when compared to ambient scenarios in terms of CO_2 emission? Implementing ramp meter control is costly; therefore, we want to know how much we could benefit from that. Here, we use the difference between optimized emission and ambient emission (i.e. not ramp meter at all) to measure the effectiveness. For example, in 40000 vehicle/hour scenario, ambient emission is 1374.66 gram, while the optimized emission is 1257.7. The effectiveness of ramp meter control is 116.76 gram per vehicle in term of CO_2 reduction. Fig. 11 plots the effectiveness as a function of traffic density. The effectiveness increases with traffic density. This result suggests implementing ramp meter control to heavy traffic density situations tend to achieve better return.

C. *Effect of Speed Limit*

From the simulation of 65mph scenario, we observed that speed is the dominant factor controlling the CO_2 emission. A direct speed control strategy is to regulate speed limit. We then conducted simulation for a series of hypothetical speed limits, i.e. 60mph and 55mph. Fig. 12, Fig. 13 and Fig. 14 displays emission result for light traffic situation (20000 vehicle/hour), moderate traffic situation (40000 vehicle/hour) and heavy traffic situation (80000 vehicle/hour), respectively.

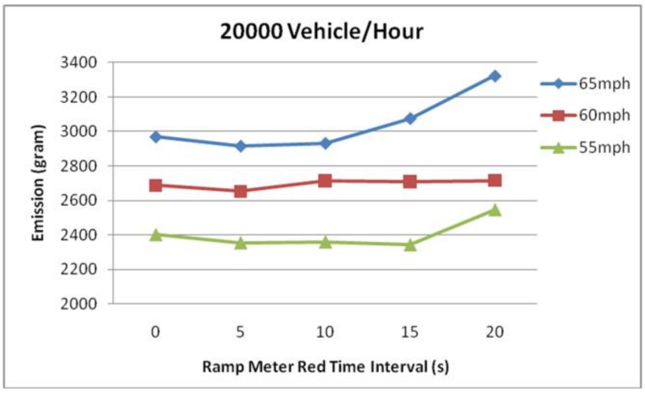

Fig. 12 Light Traffic Scenario -- Average emission is plotted as a function of red time interval, for 65mph, 60mph and 55 mph scenarios, respectively.

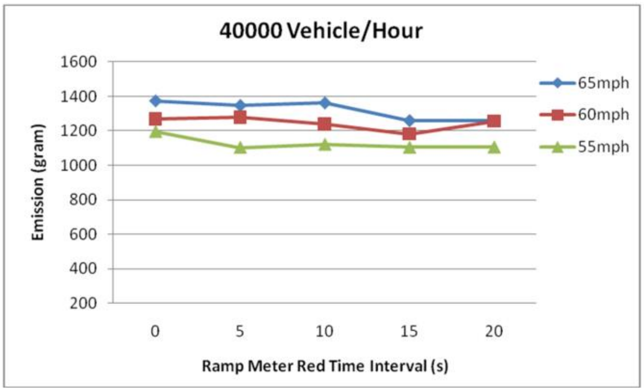

Fig. 13 Moderate Traffic Scenario -- Average emission is plotted as a function of red time interval, for 65mph, 60mph and 55 mph scenarios, respectively.

Overall, the average emission per vehicle decreases as we reduce the speed limit. This agrees with previous our previous findings, indicating speed is the dominant factor in terms of CO_2 emission. Obviously, the speed control has more significant effects on light traffic. Our results show that reducing speed limit from 65mph to 55mph could reduce the overall emission by nearly 20% for light traffic situation; but only 8% emission reduction is observed for heavy traffic situation. This is kind of opposite to ramp meter control. In previous section, we demonstrated that implementing ramp meter control works better for heavy traffic than light traffic situations.

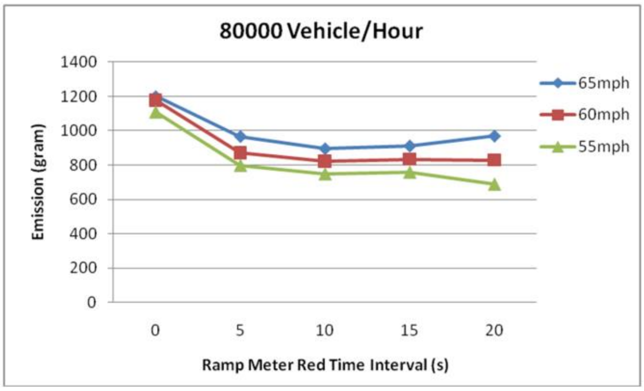

Fig. 14 Heavy Traffic Scenario -- Average emission is plotted as a function of red time interval, for 65mph, 60mph and 55 mph scenarios, respectively.

V. CONCLUDING REMARKS

We developed a microscopic model of CO_2 emission as a function instantaneous speed and acceleration. A Paramics model of a 1.5 mile 4-lane highway section containing one on-ramp (metered) and one off-ramp is developed and simulated under different traffic density scenarios and ramp meter control strategies. It is observed that in light or moderate traffic senarios, the optimal red time interval increases with traffic density. However, when the traffic becomes very heavy or jammed, the optimal red time actually decreases. Our simulation also shows the overall emission decreases with highway speed limit. The fact that the red time interval needs to be reduced under heavy traffic in order to reduce CO_2 emission indicates a trade-off between improving highway throughput and reducing CO_2 emission. Optimization plans solely targeting for higher throughput not necessarily leads to lower emission, on the contrary, it may increase the emission in some cases. It is also observed that implementing ramp meter control works better for heavy traffic than light traffic situations; while speed limit control works better for light traffic situations. This suggests implementing both active ramp meter control and active speed control could potentially minimize the average emission.

ACKNOWLEDGMENT

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