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A Fuel Economic Model Predictive Control Strategy for a Group of Connected Vehicles in Urban Roads

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Abstract— **The advancements in communication, sensing, and computing has enabled the development of *connected vehicle systems* where improved decision and control strategies are enabled with the aid of information exchange within the vehicular system. In this paper, we consider a connected vehicle system and develop fuel economic control strategies for a group of vehicles in congested urban road conditions. We exploit the Signal Phase and Timing (SPAT) information from the traffic lights and utilize model predictive control with a modified cost to reduce stopping at red lights and improve the fuel economy for a group of vehicles. The simulation results indicate the improvement in group performance for our proposed method.**

I. INTRODUCTION

With the development in the field of sensing, communication, and computing, the modern world is getting more connected and the *Connected Vehicle* paradigm is one of its examples. In the connected vehicle systems, every vehicle is capable of communicating with transportation infrastructure (V2I) and other vehicles (V2V) through wireless communication. Information such as position, speed, and acceleration of the other vehicles and traffic information, such as traffic light timing and traffic congestion information, can be made available to the communicating vehicles. This added information, apart from improving safety, is very useful in developing fuel economic control strategies especially for urban conditions.

In recent years, a lot of research in Automotive Engineering and Intelligent Transportation Systems has focused on the development of fuel economic control strategies for the vehicles. The fuel efficiency of a vehicle depends on a number of factors such as engine characteristics, vehicle structure against aerodynamic drag, powertrain system, and road and weather conditions. Apart from these factors, fuel efficiency of the vehicles has also been seen to depend on the driving behavior of the vehicles [1]. Generally, the maximum fuel economy is achieved when the acceleration and braking of a vehicle is minimized. That is why most of the control strategies on fuel economic driving focuses on driving at constant cruising velocity. Some literature in fuel economic control strategies for vehicles are available in [2], [3] where optimal cruising velocity based on vehicle's internal characteristics are being developed while a control strategy based on future road slopes is available in [4]. For different kind of terrains, authors in [5] had developed an optimal starting acceleration and cruising velocity while authors in [6] provided optimal speeding strategies for the entire driving cycle. Some of the works in developing control strategies utilizing traffic conditions are available in [1], [7], [8]. Studies and experiments involving effect of car following behaviors on emissions and energy consumptions is shown in [1] and model predictive control based strategies are provided in [7], [8], where traffic predictive frameworks are presented considering urban road conditions. The authors in [8] showed a velocity and acceleration prediction model of the preceding vehicle and the improvement in fuel economy when compared with Gipp's car model [9].

Reduction of red light idling of the vehicles have shown to improve fuel efficiency. In urban roads, traffic light plays a significant role in controlling the intersections. Although vehicle idling at red lights can be reduced by the incorporation of optimized signal timings and advanced control software in the traffic lights, they can be very costly [10]. Thus reduction of red light idling and hence improvement of vehicle fuel efficiency is better addressed from the vehicle's side. Fuel economic vehicle control utilizing traffic light conditions has got special attention among many researchers [11], [12], [13], [14]. An algorithm minimizing acceleration profile while driving through multiple signals is shown in [14]. Authors in [11] have developed a model predictive control based strategy using Signal Phase and Timing (SPAT) information that reduces red light idling and penalizes vehicle's acceleration or braking while in [12], a probabilistic decision making approach is presented. Authors in [13] has solved a similar problem for electric vehicles using a pruning and graph discretization based approach. A machine learning based approach is presented in [15] where smart phones equipped with cameras predict the phase of the traffic lights.

Most of the work in the literature focuses on developing fuel economic control strategies for a single vehicle without considering the impact of a vehicle's driving behavior to another. Apart from that, most of the algorithms using SPAT information are built for a single vehicle system without considering any road congestion. For urban road conditions, this is a very hard assumption. Although some literature [8] has considered prediction of velocity and acceleration of the preceding vehicle, such predictions might not be feasible for congested traffic conditions. For congested traffic conditions, adaptive cruise control based car following models such as *intelligent driver model* [16] and *enhanced intelligent driver model* [17] have been used in the literature but they mostly

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focus on vehicle safety rather than fuel economic driving.

In this paper, an effort has been made to develop a fuel economic control strategy for congested road conditions that focuses on reduction of red light idling using SPAT information. As pointed out in [18] that future research direction should consider vehicles as a part of a larger system, in this paper, we focus on developing fuel economic control strategies for individual vehicles that focuses on improving fuel efficiency of a group of vehicles. Although we focus on a group of vehicles, the control strategy of each vehicle is considered to be developed by each vehicle in a decentralized manner emulating the *selfish* behavior of human drivers. By modifying the cost function of the individual vehicles and considering neighborhood information exchange in the connected vehicle scenario, we show in Section IV that the fuel efficiency of a group of vehicles and the red light idling can be improved significantly. The paper is organized as follows: in Section II, we introduce the problem addressed in this paper and in Section III, we describe the decentralized control strategy that uses SPAT information and information from neighboring vehicles. Finally in Sections IV and V, we provide the simulation results and the conclusion and future works respectively.

II. PROBLEM FORMULATION

In this paper, we focus on a connected vehicle scenario with multiple vehicles in congested urban road conditions. In this connected vehicle framework, the information of position and velocity of a particular vehicle is considered to be available to the vehicle's *near neighborhood* through vehicle-to-vehicle communication. A vehicle's near neighborhood is defined as the vehicles just in front and behind a particular vehicle. The information of the neighboring vehicles can also be obtained by incorporating a radar sensor in the vehicle. Fig. 1 shows a schematic of the mentioned scenario.

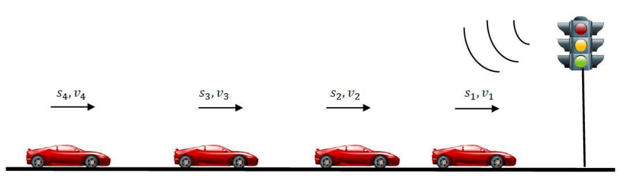


Fig. 1: Schematic of the problem

A. Vehicle Dynamics and Fuel Consumption

The vehicle dynamics of any vehicle i is given by [8]:

$$\dot{x_i} = f_i(x_i, u_i)$$
$$f_i(x_i, u_i) = \begin{bmatrix} v_i \\ -\frac{1}{2M_h^i} C_D \rho_a A_v^i v_i^2 - \mu g - g\theta + u_i \end{bmatrix} \quad (1)$$

Here $x_i = [s_i, v_i]$, and s_i is the position of a vehicle while v_i is its velocity. The control strategy, u_i, of a vehicle i at any instant is its traction or braking per unit mass. In the above equation, M_h^i, C_D, ρ_a, A_v^i, μ and θ are the mass of the vehicle, drag coefficient, the air density, the frontal area of the vehicle, the rolling friction coefficient and the road gradient respectively. Fuel consumption in a vehicle depends on a number of factors such as engine speed, torque, temperature, gear ratio and many others [7]. Deriving an exact closed form expression of fuel consumption is thus very complex and most of the literature approximates the cost of fuel consumption as a function of velocity and acceleration of the vehicle. In this paper, the fuel consumption per unit time (ml/s) is approximated by [8]:

$$Fuel_i = f^i_{cruise} + f^i_{accel} + \zeta F^i_d \quad (2a)$$
$$f^i_{cruise} = b_0 + b_1 v_i + b_2 v_i^2 + b_3 v_i^3 \quad (2b)$$
$$f^i_{accel} = \hat{a}_i(c_0 + c_1 v_i + c_2 v_i^2) \quad (2c)$$
$$\hat{a}_i = -\frac{1}{2M_h} C_D \rho_a A_v v_i^2 - \mu g + u_i \quad (2d)$$
$$\zeta = \begin{cases} 1 & \text{if } v_i = 0 \text{ or } u_i < 0 \\ 0 & \text{otherwise} \end{cases}$$

In the above equations, f^i_{cruise} and f^i_{accel} are the fuel consumed at cruising velocity and accelerating vehicle respectively. Apart from the fuel consumption due to motion, a constant fuel cost of F^i_d is considered to be associated with braking and idling at a red light [7]. The term ζ is a binary variable which is 1 during braking or idling at a red light and 0 otherwise. The terms b_0, b_1, b_2, b_3, c_0, c_1 and c_2 are constants specific to a vehicle. The fuel consumed per unit time for any vehicle i is given by Eq. (2a).

B. Finite Horizon Problem

The fuel efficiency is considered to be the fuel consumption per unit distance and for a group of n vehicles at time t, it is given by $\sum_{i=1}^n Fuel_i(t)/v_i(t)$. Generally, this problem is solved as a finite horizon problem. Considering a time horizon given by T seconds, the cost function associated with each vehicle i at each time instant k is given by [7]:

$$J_i(k) = \sum_{t=k}^{k+T-1} [w_1 \frac{Fuel_i(t)}{v_i(t)} + w_2^i(t) R_{ij}(t)^2 + w_3(v_i(t) - v^i_{target}(k))^2 + w_u u_i(t)^2] \quad (3a)$$
$$v_{min} \leq v_i(t) \leq v_{max}, \forall t \quad (3b)$$
$$u^i_{min} \leq u_i(t) \leq u^i_{max}, \forall t \quad (3c)$$
$$s_i(t) < s_j(t), \forall t \quad (3d)$$

Here, a penalty term $R_{ij}(t)$ is used to avoid collision with the preceding vehicle j. The constant $w_2^i(t)$ is chosen as $w_2^i(t) = \alpha_{w_2} e^{\beta_{w_2}(R_{ij}(t) - d_{critical})}$ so that the penalty increases as $R_{ij}(t)$ approaches $d_{critical}$, where $d_{critical}$ is a predefined distance. $v^i_{target}(k)$ is a target velocity for vehicle i at time k which is generally chosen as the road speed limit. The terms w_1, w_3 and w_u are constants dependent on the vehicle.

In Eq. (3a), the first term minimizes fuel consumption per unit distance. The second term is introduced to penalize vehicle i from getting too close to vehicle j while the third term is introduced to achieve the target or any desirable velocity. The final term penalizes amount of control used, i.e., the traction or braking generated by the powertrain of the vehicle. In the constraints shown in Eq. (3b) and (3c), v_{min} and v_{max} are the minimum and maximum velocity of the road and u^i_{min} and u^i_{max} are the limits on the control $u_i(t)$ (limits on braking and acceleration) for vehicle i. Apart the constraints shown in Eq. (3), the system constraints given by Eq. (1) is also required to be satisfied.

III. APPROACH

In this section, we describe the algorithm used to develop control strategies for the individual vehicles to improve the fuel efficiency of the group. The algorithm works in two phases: A. first a target velocity is evaluated which would enable a vehicle avoid stopping at red light, and B. a model predictive control [19] strategy is proposed which minimizes a modified cost function.

A. Target Velocity

The traffic light timings of only the approaching traffic signals are considered to be known by each vehicle and it is assumed to be noisy in nature. To avoid the noise in the traffic light timings, a green light interval (t_g) is considered which is less than the original green light time interval ($t_g < t_g^{original}$) so that the probability of getting a green light at the traffic signal within that period is almost 1.

Before running the model predictive control, the target/desired velocity of a vehicle is first chosen. Rather than choosing the target or desired velocity as the maximum allowable velocity of a road as in [8], the target velocity can be chosen wisely using SPAT information that helps the vehicle avoid stopping at red light. To reduce stoppage at red light, each vehicle is required to choose a *target velocity* ($v^i_{target}(k)$) which is computed as [11]:

$$v^i_{target}(k) = \frac{d_{ia}(k)}{g_{ab}} \tag{4a}$$

$$\text{such that } v_{min} \leq v^i_{target}(k) \leq v_{max} \tag{4b}$$

Here $d_{ia}(k)$ is the distance between $s_i(k)$ (location of the i^{th} vehicle) and the traffic signal a and g_{ab} is the time to b^{th} green signal. Thus the target velocity is a feasible velocity (given by Eq. (4b)) which is chosen to make the vehicle move past a traffic signal, a, through a *green light window*.

Apart from the evaluation of the target velocity, an allowable velocity range $[v^i_{lb}(k), v^i_{ub}(k)]$ is also chosen by each vehicle which allows the vehicle to pass the traffic signal at the green light window. The velocity range is chosen as:

$$v^i_{lb}(k) = \frac{d_{ia}(k)}{r_{ab}} \tag{5a}$$

$$\text{such that } v_{min} \leq v^i_{lb}(k) \leq v^i_{target}(k)$$

$$v^i_{ub}(k) = v^i_{target}(k) \tag{5b}$$

In the above equation, r_{ab} is the time to b^{th} red signal. According to the velocity range, considering a time step of Δt, the limits of the control input can be chosen:

$$\begin{aligned} v_i(k) &\leq v^i_{ub}(k) \\ v_i(k-1) + \breve{a}\Delta t &\leq v^i_{ub}(k) \\ \breve{a} = u_i(k) + \hat{p}_i &\leq \left(\frac{v^i_{ub}(k) - v_i(k-1)}{\Delta t}\right) \\ \text{where } \hat{p}_i &= -\frac{1}{2M_h} C_D \rho_a A_v v_i^2 - \mu g - g\theta \\ \text{similarly, } u_i(k) + \hat{p}_i &\geq \left(\frac{v^i_{lb}(k) - v_i(k-1)}{\Delta t}\right) \end{aligned}$$

Thus from the above relations, we can evaluate the limits to control input as:

$$\begin{aligned} \left(\frac{v^i_{lb}(k) - v_i(k-1)}{\Delta t}\right) - \hat{p}_i &\leq u_i(k) \\ &\leq \left(\frac{v^i_{ub}(k) - v_i(k-1)}{\Delta t}\right) - \hat{p}_i \\ \text{such that } u^i_{min} \leq u_i(t) &\leq u^i_{max} \end{aligned} \tag{6}$$

This limit on the control input suggests that if the control is bounded by Eq. (6), the velocity of the vehicle would be bounded by $[v^i_{lb}(k), v^i_{ub}(k)]$, and thus the vehicle would be able to avoid stopping at red light. It may be noted that, a feasible bounded velocity range $[v^i_{lb}(k), v^i_{ub}(k)]$, and hence a control input range does not guarantee no stoppage at red light because of the presence of high traffic in the road.

B. Model Predictive Control

In this paper, we focus on developing a decentralized control strategy for individual vehicles that would result in the improvement of fuel efficiency for a group of vehicles. We call the approach decentralized because each vehicle can solve its own control problem with the aid of local information exchange. In the field of distributed optimization and control, when a system's cost is defined as a sum of individual cost of the sub-systems (so that the cost functions are decoupled), the control variable of a sub-system is affected by another sub-system if there exists a coupling constraint that involves both the sub-systems. In this paper, the sub-systems are the individual vehicles and it can seen from Eq. (3), that the control variable of a vehicle i is dependent on the position of its preceding vehicle j so as to maintain the constraint in Eq. (3d). This is reflected in the cost function of individual vehicles through the term $R_{ij}(t)$ and w_2 in Eq. (3a). It may be noted here that for a congested traffic conditions and since every vehicle's state and control is influenced by its preceding vehicle, the state and control variable of any vehicle depends directly or indirectly on the state of all the vehicles in front of it.

To avoid stopping at red lights, achieving the target velocity is essential. Thus for a group vehicles, the total red light idling time would be dependent on the number of vehicles able to reach and maintain its allowable velocity range $[v^i_{lb}, v^i_{ub}]$ as defined in Section III-A. To do that, we modify the cost of individual vehicles in Eq (3a) at each time step k as shown in the following equation:

$$
\begin{aligned}
J_i(k) = & \sum_{t=k}^{k+T-1} [w_1 \frac{Fuel_i(t)}{v_i(t)} + w_2^i(t) R_{ij}(t)^2 \\
& + w_3 (v_i(t) - v_{target}^i(k))^2 + w_u u_i(t)^2 \\
& + w_4 (v_{target}^l(k) - v_i(t))]
\end{aligned} \tag{7a}
$$

$$v_{lb}^i(k) \leq v_i(t) \leq v_{ub}^i(k), \forall t \tag{7b}$$

$$\hat{u}_{min}^i \leq u_i(t) \leq \hat{u}_{max}^i, \forall t \tag{7c}$$

The terms $v_{lb}^i(k)$ and $v_{ub}^i(k)$ are evaluated as described in Section III-A and $\hat{u}_{min}^i$ and $\hat{u}_{max}^i$ are evaluated from Eq. (6). In Eq. (7a), the term $v_{target}^l(k)$ is the target velocity, similar to its own target velocity $v_{target}^i(k)$, of the vehicle l behind the vehicle i. Since the information of the position and velocity of the neighboring vehicles, vehicle j and l in front and behind respectively, are available to each vehicle, the target velocity of the vehicle l ($v_{target}^l(k)$) can also be computed by vehicle i.

The term $(v_{target}^l(k) - v_i(t))$ can be interpreted as a *safety term* employed by vehicle i to avoid collision with the vehicle l behind it when it would reach its target velocity $v_{target}^l(k)$. This term $(v_{target}^l(k) - v_i(t))$ apart from acting as a safety factor, helps in achieving the target velocity of the vehicle l behind it and in the process would help the vehicle l in avoiding stopping at red light. The weight w_4 is chosen as $w_4 = 0$ when $(v_{target}^l - v_i(t)) \leq 0$, i.e., when the current velocity of vehicle i is higher that the target velocity of vehicle l. The w_4 is chosen as a function of distance as shown in the following equation:

$$w_4 = \begin{cases} 0 & \text{if } v_{target}^l \leq v_i(t) \\ \alpha_{w_4} e^{(-\beta_{w_4}(s_i(t) - s_j(t)))} & \text{Otherwise} \end{cases} \tag{8}$$

Here, α_{w_4} and β_{w_4} are constants. It is evident from the above equation that w_4 increases as $(s_i(t) - s_j(t))$ decreases and vice versa. The new control algorithm thus would *push* a vehicle to let the vehicle behind it achieve its target velocity. Although this penalty of driving slower than the target velocity of the vehicle behind is added, the velocity of a vehicle will not violate the constraints in Eq. (7b) and Eq. (6) and so will not jeopardize the vehicle's ability to pass through the signal without stopping at red light. It may be noted here, that there would be a saturation and some vehicles will not be able to cross a traffic signal at a given green light window even though they evaluate feasible target velocity and control input bounds because of the road safety and constraints present because of congested traffic. In our control strategy, we try to increase the number of vehicles passing through a given green light window. In this paper, we use the widely used *sequential quadratic programming* [20] for solving the non-linear optimization problem described in Eq. (7).

IV. SIMULATION RESULTS

In this section, we present the simulation results of the methodology explained in Section III. The simulation scenario considered in this paper is a single lane road with traffic lights at every 1 km (1000 meter). Each vehicle implements a model predictive controller as defined by Eq. (7) so that: i) each vehicle minimizes its own fuel consumption per unit distance, ii) avoids collision with other vehicles and iii) Avoids stopping at red lights.

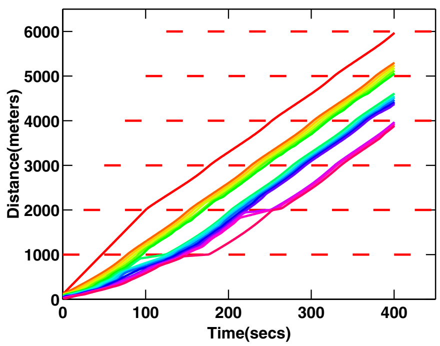
The simulation is run for 400 seconds where a prediction horizon $T = 5$ seconds is used and a time step of 0.5 seconds is considered. Most of the simulation parameter terms are taken from [7] and [8]. All the vehicles are considered to be identical with $M_h^i = 1200$ kg, $A_v^i = 2.5\ m^2$ and $u_{max}^i = 3\ m/s^2, \forall i$. The parameters related to the environment are: $C_D = 0.32$, $\rho_a = 1.184\ kg/m^3$ and $\theta = 0$ degree. The fuel consumptions parameters are considered to be $b_0 = 0.1569$, $b_1 = 2.450 \times 10^-2$, $b_2 = -7.415 \times 10^-4$, $b_3 = 5.975 \times 10^-5$, $c_0 = 0.07224$, $c_1 = 9.681 \times 10^-2$, $c_2 = 1.075 \times 10^-3$ and $F_d^i = 0.1, \forall i$. The actual green and red light time intervals are considered to be $t_g^{original} = 30$ seconds and $t_r^{original} = 20$ seconds respectively and the truncated green light interval is considered to be $t_g = 25$ seconds to address the noise in traffic light signal information. The maximum allowable velocity v_{max} is considered to be 20 m/s while the minimum velocity is considered to be v_{min} = 0 m/s.

In this paper, we have focused on developing fuel economic control strategies for a group of vehicles, and so we compare our modified algorithm as described in Section III with traditional model predictive control framework with SPAT information. We call *Approach 1*: the method solving the traditional model predictive control cost, in Section II-B, with SPAT information, and *Approach 2*: the method solving the modified cost in Section III-B and SPAT information. In both the approaches, the target velocity is computed using the traffic timing information. We provide two separate simulation examples with different number of vehicles in the road: i) 15 vehicles, and ii) 25 vehicles.

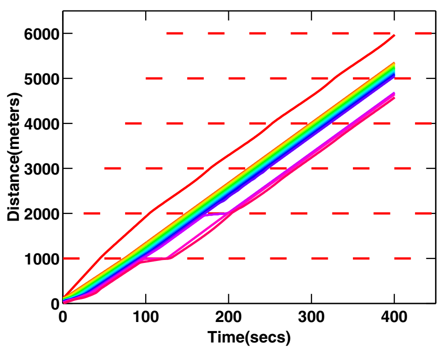
Case 1: 15 vehicles: Here 15 vehicles are considered for simulation purposes. The initial locations of the vehicles as well as their initial velocities are randomly chosen. Fig. 2 shows the trajectory of all the vehicles for 400 seconds where results in Fig. 2a uses Approach 1 and Fig. 2b uses Approach 2. In can be seen from Fig. 2, that since Approach 2 incorporates the driving behavior of the vehicle behind, more vehicles can pass through a particular green light window. The comparative results of Approach 1 and Approach 2 are listed in Tab. I and Tab. II. From Tab. I it can seen that the total fuel consumption for the whole group of 15 vehicles is substantially less when using Approach 2 and the mean velocity of almost all the individual vehicles are higher for their entire trajectory when using Approach 2. From Tab. II, it can be seen that the average distance traveled and the total stoppage at red lights are improved when using Approach 2. The velocity profile of few vehicles which consumed much higher fuel when using Approach 1 are shown in Fig. 3 and Fig. 4. It is evident from the figures that the oscillation about a mean in the velocities lead to a higher fuel consumption.

Case 2: 25 Vehicles: Here 25 vehicles are considered for simulation purposes. Similar to Case 1, the initial locations of the vehicles as well as their initial velocity are randomly chosen. Fig. 5 shows the trajectory of all the vehicles for 400 seconds where results in Fig. 5a uses Approach 1 and Fig. 5b uses Approach 2. In Tab. III and IV, it can seen that Approach 2 leads to better mean fuel and hence total fuel consumption, higher average velocity, higher distance traveled and less stoppage at red light for the group of 25 vehicles.

We run the simulation results in Matlab R2013a on a computer with i7-4702MQ processor. At each time step, the computation time of the algorithm on average is approximately 0.38 seconds.



(a) Approach 1

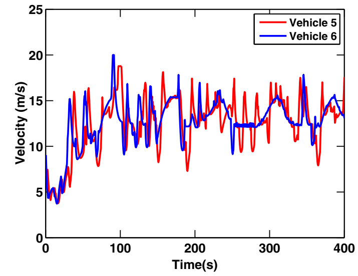


(b) Approach 2

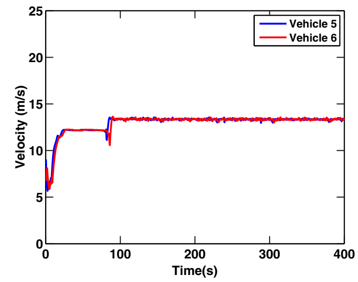
Fig. 2: Vehicle Trajectories in Case 1

TABLE I: Case 1: Individual Vehicle Comparison after 400 seconds

Vehicle No.	Average Velocity (m/s)		Fuel Consumption (ml)	
	Approach 1	Approach 2	Approach 1	Approach 2
1	14.60	14.60	265.23	267.53
2	12.95	13.09	237.55	214.56
3	12.82	13.03	263.79	255.63
4	12.71	12.99	287.70	258.59
5	12.57	12.93	372.80	252.20
6	12.46	12.89	370.84	252.91
7	11.36	12.85	285.51	254.35
8	11.23	12.79	284.99	251.51
9	11.16	12.73	313.23	250.76
10	11.04	12.67	338.95	258.21
11	10.94	12.62	329.69	253.82
12	10.86	12.56	332.01	301.69
13	9.87	11.66	273.53	238.57
14	9.79	11.59	274.66	256.53
15	9.70	11.43	255.80	256.31
Total:			4486.4	3823.3

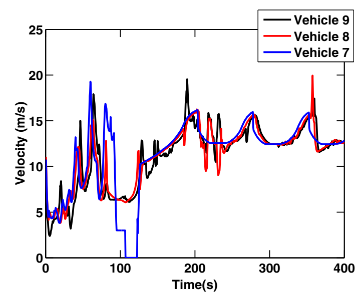


(a) Approach 1

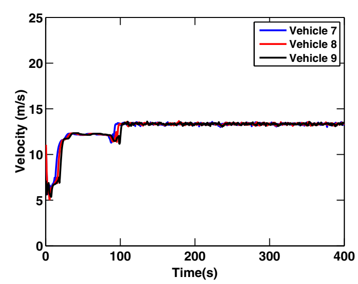


(b) Approach 2

Fig. 3: Velocity vs Time



(a) Approach 1



(b) Approach 2

Fig. 4: Velocity vs Time

TABLE II: Case 1: System Comparison after 400 seconds

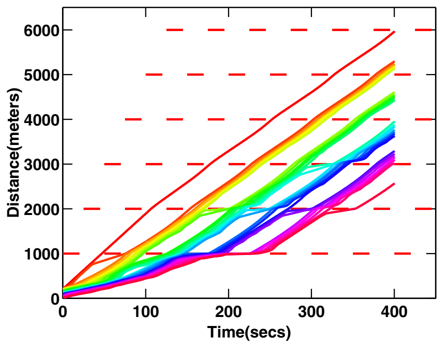
Average Distance (m)		Total Red Light Idling (secs)	
Approach 1	Approach 2	Approach 1	Approach 2
4705.3	5142.4	61	35

TABLE III: Case 2: System Comparison after 400 seconds

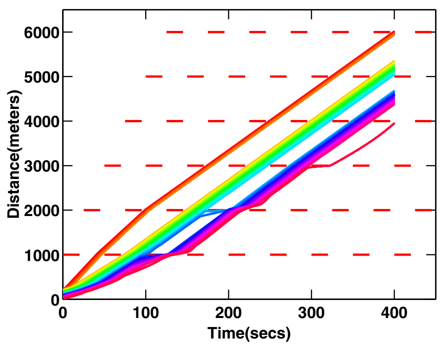
Average Velocity (m/s)		Mean Fuel Consumption (ml)	
Approach 1	Approach 2	Approach 1	Approach 2
9.96	12.15	289.65	260.47

V. CONCLUSIONS

In this paper, a decentralized fuel economic control strategy is presented that focuses on reduction of red light idling



(a) Approach 1



(b) Approach 2

Fig. 5: Vehicle Trajectories in Case 2

TABLE IV: Case 2: System Comparison after 400 seconds

Average Distance (m)		Total Red Light Idling (secs)	
Approach 1	Approach 2	Approach 1	Approach 2
4103.5	4980.3	300	58

and improvement of fuel economy for a group of vehicles. The proposed method considers a connected vehicle scenario so that the Signal Time and Phase information of the traffic signals can be considered to be available to the individual vehicles. Apart from that, the information of the states of the vehicles in the neighborhood of a vehicle is considered to be known knowledge. Our proposed method tries to reduce red light idling by allowing a greater number of vehicles pass through a given green light window, and by doing so it helps in maintaining a near constant velocity for a larger number of vehicles. The simulation results presented in Section IV shows the improvement in group performance from the proposed method. One of the future research direction includes development of probabilistic decision making techniques for a congested traffic condition in urban roads for further reduction in red light idling and hence improvement in fuel economy. Another research direction would be to implement the proposed method in a larger urban vehicular network and develop improved control strategies for the vehicles when information in the system increases.

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