UC Riverside
2019 Publications

Title
Developing an Adaptive Strategy for Connected Eco-Driving under Uncertain Traffic Condition

Permalink
https://escholarship.org/uc/item/2mg7604m

Authors
Wei, Zhensong
Hao, Peng
Barth, Matthew J

Publication Date
2019-06-01

DOI
10.1109/IVS.2019.8813819

Peer reviewed

eScholarship.org Powered by the California Digital Library
University of California

2019 IEEE Intelligent Vehicles Symposium (IV)
Paris, France. June 9-12, 2019

Developing an Adaptive Strategy for Connected Eco-Driving under Uncertain Traffic Condition

Zhensong Wei, Peng Hao, *Member, IEEE*, and Matthew J. Barth, *Fellow, IEEE*

***Abstract*—The eco-approach and departure (EAD) application for signalized intersections has been proved to be environmentally efficient in a Connected and Automated Vehicles (CAVs) system. The traffic and signal phase and timing (SPaT) information transmitted from the roadside equipment unit, vehicle equipped sensors (e.g. radars) and other connected vehicles are the main inputs to the existing algorithms. However, due to the limitation of the communication and sensing range, it is too late to start eco-driving until preceding traffic is fully detected. Instead, the historical data, such as queue length distribution may be applied to developing a robust speed profile that enables eco-driving to start in an early stage. In this paper, a two-phase iterative approach is developed with the use of historical queue distribution. A graph-based model is created with nodes representing states of the host vehicle and traffic condition, and directed edges with weight representing expected energy consumption between two connected states. The shortest path is calculated that minimizes the total energy consumption for vehicles approaching a pre-timed signalized intersection. Numerical simulations have shown that the proposed method is robust and adaptive to varying traffic and queue conditions, and could achieve around 9% energy savings compared to other baseline methods.**

I. Introduction

THE rapid development of transportation activities has been not only substantially increasing people's mobility, but also producing more greenhouse gas (GHG) emissions and consuming a large amount of energy. In 2016, it is estimated that transportation sector has accounted for the largest portion (28%) of total U.S. GHG emissions, with 83% of the gas emitted by light-duty vehicles and medium- and heavy-duty trucks [1]. According to the statistics from U.S. Department of Energy, the energy consumption of transportation has kept increasing since 2012, reaching 28.2 quadrillion Btu (British thermal unit) and a share of 28.8% of U.S. total energy consumption by end-use sector in 2017 [2]. The increasing energy consumption and GHG emissions have drawn tremendous attention of government and researchers, and a series of eco-driving projects and applications has come up throughout the years to improve the efficiency of the transportation system. In Europe, starting from 2010, the project eCoMove has developed a transport energy efficiency system based on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I/I2V) communication, where real-time data can be shared among the vehicles and traffic controllers supporting a more fuel-saving traffic system [3]. In the U.S., Application for the Environment: Real-Time Information Synthesis (AERIS) research program established by the Intelligent Transportation Systems (ITS) Joint Program Office (JPO) in 2014 has developed 18 Connected Vehicle (CV) applications in 5 Operational Scenarios, among which Eco-Approach and Departure (EAD) at Signalized Intersections has been proven to be an effective application in decreasing fuel consumption and emissions [4].

Zhensong Wei, Peng Hao, and Matthew J. Barth are with the College of Engineering – Center for Environmental Research and Technology (CE-CERT), University of California, Riverside, CA 92507, USA. Email: zwei030@ucr.edu, haop@cert.ucr.edu, barth@ece.ucr.edu

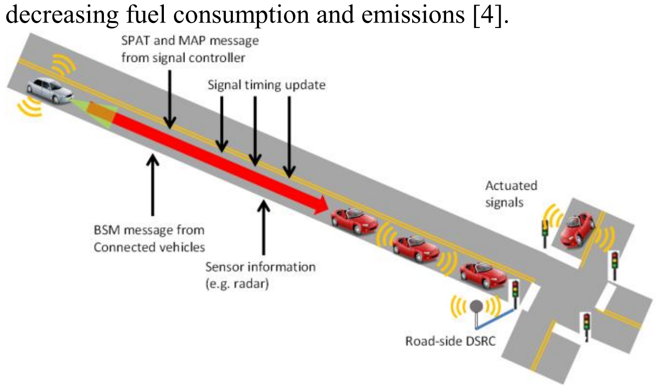

Figure 1. Dynamic information in connected eco-driving.

The EAD application in the host CV can calculate the most energy efficient speed profile and guide the vehicle to pass the target traffic signal in an eco-friendly manner after collecting the Basic Safety Message (BSM) from other CVs and Signal Phase and Timing (SPaT) information transmitted from the roadside equipment unit [5]. Besides the SPaT messages and traffic condition (number of queued vehicles or queue length) that serve as a main requirement for the application, other types of information such as geographic data (road map and grade) and vehicle dynamics also contribute to the calculation of an ideal speed profile. In real-world traffic, as shown in Fig. 1, signal timing and traffic conditions usually appear to be dynamic and uncertain. For example, when a CV is approaching an actuated signalized intersection, the remaining time of the current signal phase indicated by the SPaT message will be updated dynamically. And the traffic-related information received from other CVs and radar is also highly uncertain due to the limited sensing range and varying driving behaviors of other vehicles. Therefore, the future signal timing and traffic condition of the downstream intersection is hard to predict, which brings challenges to develop applicable EAD models.

The EAD application was initially developed under fixed-timing signal control, which 12% reduction on fuel consumption and CO_2 emissions have been validated in microscopic simulation models [6]. Later studies also made no-preceding traffic or fixed-timing signal assumptions to avoid the uncertainty in the traffic condition [5, 7]. He et al. obtained the speed profile by solving a multi-stage optimal function and put the queue information into constraints [8], Ye et al. estimated the end of queue based on the predicted preceding vehicle trajectories, with an assumption under congested urban traffic scenario such that a preceding vehicle could always be detected after SPaT messages are received [9]. All the above studies were conducted under the assumption that either queue does not exist or is fully predictable before trajectory planning. If the radar does not have enough sensing range to detect the preceding vehicle after signal information is received, those studies will not be able or will be less effective to design an optimal speed profile for drivers or longitudinal controller to follow.

In this paper, we propose a two-phase iterative approach to adapt the uncertain queue information so that the vehicle could start eco-driving once entering the DSRC range even without knowing the current queue information. The first phase creates the speed profile after detecting the end of queue based on the information acquired from I2V/V2V communication (DSRC or messages from NPV if it is also a CV) and onboard sensors (radar). The second phase derives the speed profile starting from the receiving of the SPaT messages to the detection of the end of queue, through analyzing the signal information and potential traffic condition based on historical data (queue distribution). The most energy-efficient solution can be then derived from minimizing the expectation of the energy consumption of all possible actions after combining the two phases. The paper is organized as follows: Section II presents a detailed description of the proposed method. Section III shows the numerical simulation results with comparisons of other methods and the last section concludes the paper with further discussion.

II. METHODOLOGY

A. Problem statement

When a CV approaches within the range of Dedicated Short Range Communications (DSRC) roadside equipment unit of a signalized intersection, it could receive SPaT information and know the status of current traffic signal with the starting and remaining time for the current phase. If the preceding vehicles are within the detection range of the CV equipped radar, the speed and the location of that vehicle could be measured, and the stop location of the queue could be determined if the measured speed reaches zero. We not only want the designed speed profile to be energy efficient, but also causing no delay to the following traffic, since the delay might force the following vehicles to slow down and result in both safety and energy waste problem. Therefore, the host vehicle should pass the traffic signal right after the nearest preceding vehicle (defined as NPV) in the same lane with an energy efficient manner.

There are several scenarios that the vehicle might enter if trying to pass the signalized intersection after receiving the SPaT information. If the current signal is green and NPV is detected to be moving, the host vehicle could follow the NPV with an eco-adaptive cruise control strategy. If the current signal is green and NPV is detected to stop, then the estimated time that vehicle should arrive at the intersection could be calculated from the starting time of the current signal phase with extra reaching time depending on the location of the stop caused by the shockwave theory. If the current signal is red then NPV is most likely to be detected to a stop at some time during the trajectory, and the radar sensing range together with the distance between NPV and host vehicle restricts the distance of eco-driving. For all the cases discussed above, the NPV's stop location is crucial to determine the optimal speed profile for the host vehicle as it affects the location and time when eco-driving could start and finish. However, due to the radar's limited sensing range (most likely smaller then DSRC range), the host vehicle is usually very close to the queue when the NPV is detected to a stop and it is too late to start eco-driving at that moment. To start the trajectory planning at an earlier stage when SPaT messages are first received, we must deal with the partially observed traffic condition, or the uncertain queue position.

The proposed method divides the process into two parts which are separated by the time that the stop of NPV is detected. The first part involves the uncertainty of the traffic condition and the second part is deterministic with trajectory always reaching an absolute optimal. Therefore, we first construct the graph of the second part of the process and name it as Phase I, and then the graph of the first part of the process can be derived based on the original graph, which is named as Phase II. In the graph, the nodes represent different states of the vehicle and traffic condition, and directed edges with weight representing expected energy consumption between two connected states. A state points to four properties, which are distance to traffic signal (d_{TL}), passing time after SPaT is first received (t), speed (v) and number of cars queuing by the traffic signal (Q). Two nodes can be connected if the vehicle can reach from one state to another in the minimum time interval (Δt). And for a certain state, as long as the predefined final state is reachable, the next state the vehicle visits in the best solution path is always stable. For example, for a state with parameter [$d_{TL} = d_1, t = t_1, v = v_1, Q = Q_1$], the next state it could visit has parameter [$d_{TL} = d_1 - v_1 \times \Delta t, t = t_1 + \Delta t, v = v_2, Q = Q_1$] and v_2 should be deterministic if the state is in the best solution path. And the iteration over all possible states is to guarantee the minimum energy path chosen correctly.

As aforementioned, the proposed iterative method can be divided into two phases. In the first phase, we want to derive an optimal speed profile for the trajectory under the condition of known queue. This includes the position of host vehicle from the point that queue can be first detected by the radar until the vehicle reaches the traffic light ($0 \leq d_{TL} \leq d_{Rad} + max(L_{Queue})$, where d_{Rad} is the sensing range of radar and L_{Queue} is the queue length by the traffic signal depending on the length per vehicle and number of vehicles). And in the second phase, we want to derive the trajectory speed profile under the condition of unknown queue. This includes the position from the point that SPaT information is first received until the latest point that queue can be first detected ($min(L_{Queue}) + d_{Rad} \leq d_{TL} \leq d_{DSRC}$, where d_{DSRC} is the communication range of DSRC). Fig. 2 shows a sample trajectory of the two phases for a vehicle approaching the traffic signal where there is a queue waiting by. Implementation details of the two phases are given in subsections B and C.

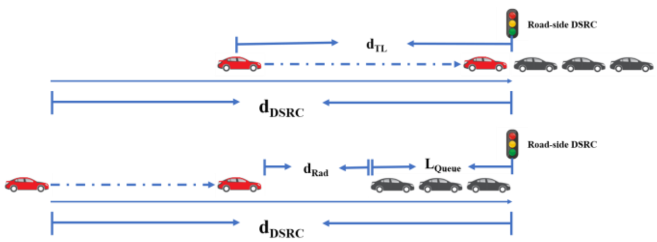

Figure 2. Sample trajectory of a host CAV (red) approaching the traffic signal in two phases, trajectory in Phase I (top row) and Phase II (bottom row) can be combined into a complete trajectory.

B. *Phase I*

First, we define all possible states in the vehicle trajectory and initialize a state-energy matrix M of size N by 2, where N is the total number of states. For a given state in the matrix, the first entry represents the minimum energy the vehicle will consume leaving that state for a predefined final state, and the second entry represents the state of next time step that host vehicle should reach to minimize the total energy. All the state parameters are discrete, and N is defined as such:

$$N = \text{size}(0{:}\Delta d_{TL}{:}\max(d_{TL})) \times \text{size}(0{:}\Delta t{:}\max(t)) \times \text{size}(0{:}\Delta v{:}\max(v)) \times (\text{size}(0{:}\Delta Q{:}\max(Q)) + 1) \quad (1)$$

which Δd_{TL}, Δt, Δv and ΔQ are the minimum interval in the four state parameters respectively. The extra count in Q states points to the circumstance that queue hasn't been detected by radar ($Q_{Unknown}$) and corresponds to the state of queue in the second phase.

Then we initialize the final state in M, which is the state the vehicle will end up with in the trajectory under each different known queue condition, corresponds to the state:

$$d_{TL} = 0,\ t = t_{SPaT} + t_{shock\ wave},\ v = v_t,\ Q = 0{:}\Delta Q{:}max(Q) \quad (2)$$

where t_{SPaT} is the remaining time traffic signal going to turn green indicated by the SPaT information received at the beginning of the trajectory. $t_{shock\ wave}$ is the extra reaching time caused by the shockwave theory and is a function of Q.

After the initialization is done, iterative approaches are conducted to modify M. We first find the states that are directly connected to the final state and calculate their energy consumptions, then states connected to the previous states are found out and minimum energy consumptions are calculated through comparison of possible connections. Through such iteration, a trajectory for the vehicle reaching the final state under the condition of known queue from any initial condition can be decoded from M. The pseudocode for Phase I is shown as below:

```
function Phase I:
flag = 1
while flag = 1:
    flag = 0
    for each state in M that Q is known, denote as State1:
        for each possible state that could reach State1 in the
        next time step, with the same Q, denote as State2:
            calculate energy(E) vehicle required reaching
             State1from State2
            update M if E+ M(State1,1) < M(State2,1) with:
                M(State2, 1) = E+ M(State1,1)
                M(State2, 2) = State1
                flag = 1
        end
    end
end
```

The energy (E) is the tractive power the vehicle spends reaching State1 from State2, which relates to the speed of the two states. The use of flag is for indicating whether there is any update after iterating over all the states in the trajectory. If there is at least one update in the previous loop, the Phase I function will iterate through all the states once again to ensure all the state points finding a minimum energy trajectory to the final state.

C. *Phase II*

In Phase II, we continue modifying M for the states whose queue hasn't been detected. For the current state (State1) that queue is unknown, at next time step with a given speed, all the state parameters (State2) that vehicle will enter are stable except the queue state is either known (queue detected by radar) or still unknown. For each location in the trajectory that queue is unknown, there is a pool of possible queue depending on d_{TL}, and the pool of a state with smaller d_{TL} is always a subset of the pool whose state has a larger d_{TL}. Therefore, we can define the queue pool for State1 as [0, 1, 2, … Q_k], and queue pool for State2 as [0, 1, 2, … Q_n], k>= n, and obtain the following probability equation:

$$P[state(Q=Q_k)|state(S_2)] + \ldots + P[state(Q=Q_{n+1})|state(S_2)] + P[state(Q \in [0,1,\ldots,Q_n])|state(S_2)] = P[state(Q \in [0,1,\ldots,Q_k])|state(S_1)] \quad (3)$$

where S_1 is the state parameter [$d_{TL} = d_1,\ t = t_1,\ v = v_1$], S_2 is the state parameter [$d_{TL} = d_1 - v_1 \times \Delta t,\ t = t_1 + \Delta t,\ v = v_2$] and State(S) represents the state with labeled parameters S. The probabilities can be calculated from the historical queue distribution of the road.

According to (3) and M, the energy expectation for reaching the final state from State1 is calculated and used as part of the update criterion in Phase II, shown as below:

$$P[state(Q=Q_k)|state(S_2)]*(E+M[state(Q=Q_k,S_2),1])$$
$$+...P[state(Q=Q_{n+1})|state(S_2)]*(E+M[state(Q=Q_{n+1},S_2),1]) \quad (4)$$
$$+P[state(Q=Q_{unknown})|state(S_2)]*(E+M[state(Q=Q_{unknown},S_2),1])$$

A similar iterative approach is conducted, and a trajectory for the vehicle entering the DSRC range till the vehicle detects the queue can therefore be decoded from M.

III. RESULTS

Simulations are conducted in MATLAB to test the proposed method and compare with the baseline. Table 1 below shows the assumptions for all the simulations.

TABLE 1. Simulation Assumptions and Parameters.

d_{DSRC}	Communication range	300 m
$t_{shock\ wave}$	Additional time from shockwave	0 s if Q = 0, else 2(Q+1) s
v_0, v_t	Initial and final speed of the host vehicle	13 m/s
v_{max}	Maximum speed	18 m/s
v_{min}	Minimum speed	0 m/s
a_{max}, - a_{min}	Maximum and minimum acceleration	2 m/s^2
Q	Number of Queueing vehicles	**Z**[0, 20]
Δd_{TL}, Δt, Δv, ΔQ	minimum interval in the state parameters	1
Vehicle length	length per vehicle	5 m/vehicle

The ideal trajectory for absolute minimum energy consumption can be derived from M when the real queue length is known (i.e. perfect information) at the same time as first SPaT message being received, for example: $d_{Rad} = d_{DSRC}$. Besides the ideal method, couple of baseline methods (Baseline$_k$) are setup for comparison: Assuming the queue length to be Q_k, the vehicle first follows the ideal trajectory of assumed Q_k, length, then change to the corresponding strategy after detecting the real queue length. These baselines are the methods given the same information as the proposed method except the historical queue distribution is missing. Note that if k is 0, Baseline$_0$ corresponds to the scenario when the vehicle follows the existing EAD strategy with no-queue assumption until the radar detects preceding traffic.

Note that for some baseline methods, there might not exist a solution, for example: the vehicle is first driven at an assumption of a large queue length, but the real queue length is small, therefore the vehicle will first drive at a relatively lower speed due to the assumed long $t_{shock\ wave}$ and couldn't reach the traffic signal at required time after real queue is detected. In these cases, a delayed time (t') can be calculated as the minimum extra time that vehicle is given to finish the trajectory with predefined final speed v_t. This delayed time will also force the following vehicles to slow down and result in extra energy and fuel consumption to the system. To quantify the delayed time as the amount of energy ($E_{penalty}$), the following method is applied:

E_1 = energy consumption for vehicle running t_1 sec at v_t m/s.

E_2 = minimum energy consumption for vehicle running the same distance ($t_1 \times v_t$) in time (t_1 - t') with same initial and final speed v_t m/s under a certain maximum speed and restricted acceleration.

$E_{penalty} = E_2 - E_1$

Therefore, all the methods including ideal, proposed and baseline can be evaluated with energy consumption and the result is shown in the following subsections.

A. Sample trajectory among different methods

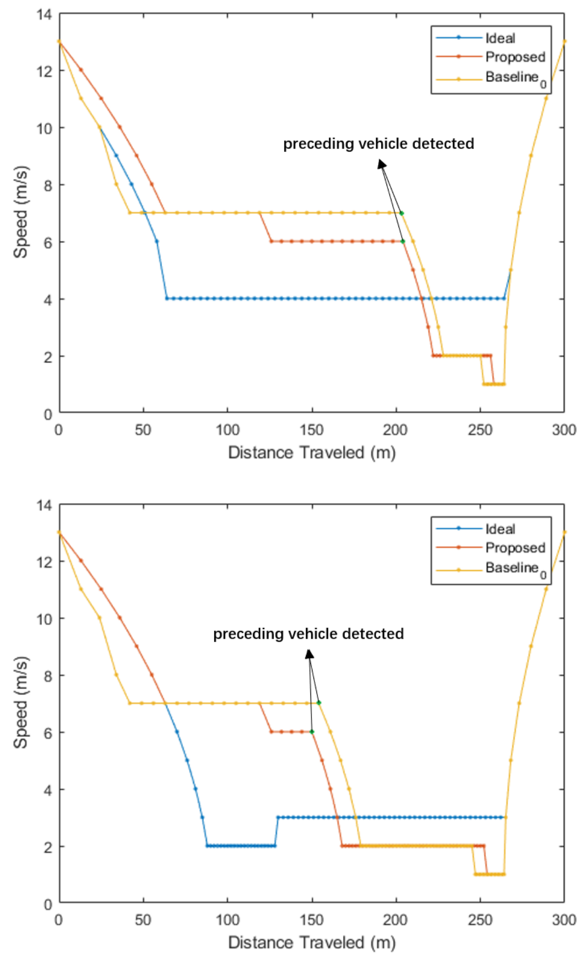

Figure 3. Speed profile of proposed against baseline and ideal method with Q = 10 (top) and 20 (bottom). Note that Baseline$_0$ (and proposed) method result in the same trajectory in the two plots before preceding vehicle getting detected (point labeled with green). Compared to the baseline method, the proposed method spends shorter time driving at higher constant speed, which saves 2.28% (top) and 2.17% (bottom) total energy respectively.

First, two sample trajectories of the vehicle approaching traffic signal with different queue lengths derived from each method are shown in Fig. 3. For the baseline method, zero vehicle is assumed to be waiting by the traffic signal and Baseline$_0$ is used. The other assumptions include: d_{radar} = 50m, t_{SPaT} = 40s and $Q \sim unif\{0, 20\}$.

B. Performance comparison of energy consumption

We first compare the energy consumption among different methods for varying exact queue length. All the parameters except real queue length are set as constant values, including:

$$d_{radar} = 100\text{m},\ t_{SPaT} = 40\text{s and } Q \sim unif\{0, 20\} \quad (5)$$

As shown in Fig. 4, the proposed method has a lower energy consumption than the baseline methods for most Q and only has a slightly larger energy consumption compared to the ideal method. To compare with all the possible baseline methods, since the Q distribution is uniform, the expected energy consumption (E_{Exp}) is calculated as the average consumption value of all Q, and is shown in Table 2. We can see that the proposed method reduces energy consumption by 3.35% (Baseline0) and 8.88% (average 21 baselines) and is 2.24% higher than the ideal energy consumption.

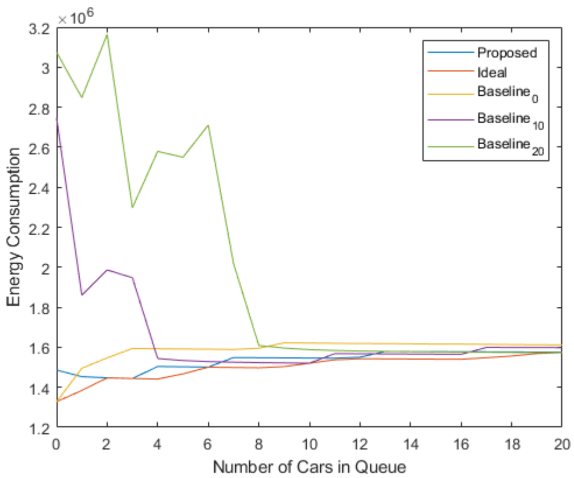

Figure 4. Energy comparison (y axis) of proposed against baseline and ideal method in terms of different queue length (x axis)

TABLE 2. Expected Energy Consumption (E_{Exp}) Comparison among Proposed, Baseline and Ideal Method.

Method	Energy(10^6)	Method	Energy(10^6)
Ideal	1.5011	Baseline_{10}	1.6682
Proposed	**1.5354**	Baseline_{11}	1.6998
Baseline_{0}	1.5869	Baseline_{12}	1.6235
Baseline_{1}	1.5500	Baseline_{13}	1.6506
Baseline_{2}	1.5444	Baseline_{14}	1.6727
Baseline_{3}	1.5417	Baseline_{15}	1.7176
Baseline_{4}	1.5424	Baseline_{16}	1.7365
Baseline_{5}	1.5646	Baseline_{17}	1.7949
Baseline_{6}	1.5932	Baseline_{18}	1.8532
Baseline_{7}	1.6156	Baseline_{19}	1.9315
Baseline_{8}	1.6066	Baseline_{20}	1.9908
Baseline_{9}	1.6216		

We then compare the energy consumption among different methods for varying t_{SPaT}, meaning diverse time the vehicle enters the DSRC range and approaches the traffic signal. The same parameters are used except t_{SPaT} (20~60s).

For the ideal method, as shown in Fig. 5, E_{Exp} is monotonically increasing due to the more frequent acceleration and deceleration during longer travel time. The proposed method shows a better performance than baseline methods when $t_{SPaT} \geq 22$s. The worse performance for small t_{SPaT} is caused by the high acceleration and speed of the vehicle that tries to arrive at the traffic signal at the required time. The energy consumption tends to reach the same value as t_{SPaT} increases among all methods.

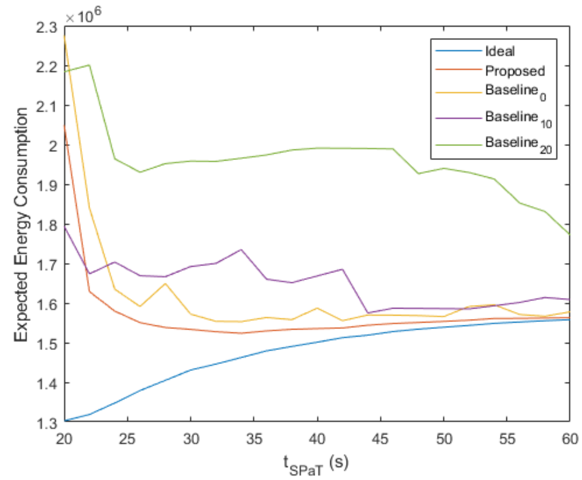

Figure 5. E_{Exp} comparison (y axis) of proposed against baseline and ideal method in terms of different t_{SPaT} (x axis)

C. Comparison of methods for varying d_{Rad}

In this subsection, we want to compare the energy consumption among different methods for varying d_{Rad}. This simulates the various sensing range of all kinds of radars or when there is a preceding vehicle stopping in front of the host vehicle. The same parameters are used as (5) except d_{Rad} (50~200m).

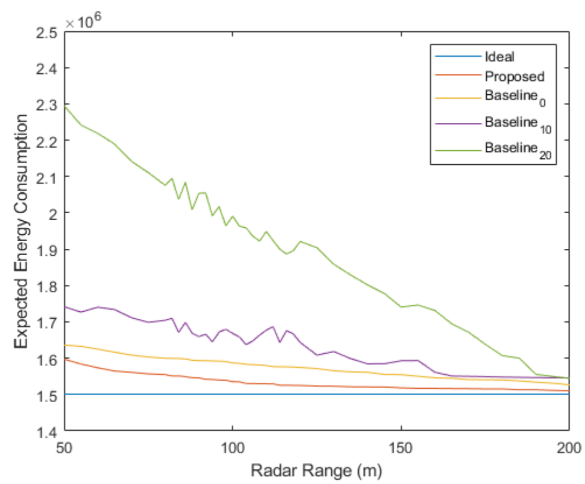

Figure 6. E_{Exp} comparison (y axis) of proposed against baseline and ideal method in terms of different radar range (x axis). We can observe more energy saving when radar range is shorter.

As we can see from Fig. 6, the proposed method always outperforms the baseline method. E_{Exp} of ideal method stays the same for all radar range since the queue length is set to be known from the beginning. For both baseline methods and proposed method, E_{Exp} gradually decreases as d_{Rad} increases, since the distance that queue is known gets longer and a larger portion of the trajectory can result in absolute minimum energy consumption. A detailed E_{Exp} table is shown in Table 3. We can see that the proposed method consumes less energy for every d_{Rad} compared to the baselines.

TABLE 3. E_{Exp} (10^6) Comparison between Proposed, Baseline and Ideal Method for Different d_{Rad}.

Method / d_{Rad}	Ideal	**Proposed**	Baseline_0	Baseline_{10}	Baseline_{20}
50	1.5011	**1.5973**	1.6360	1.7419	2.2949
60	1.5011	**1.5735**	1.6249	1.7403	2.2186
70	1.5011	**1.5610**	1.6085	1.7115	2.1418
80	1.5011	**1.5549**	1.5998	1.7043	2.0755
90	1.5011	**1.5461**	1.5933	1.6593	2.0540
100	1.5011	**1.5354**	1.5869	1.6682	1.9908
110	1.5011	**1.5297**	1.5797	1.6770	1.9489
120	1.5011	**1.5250**	1.5744	1.6438	1.9214
130	1.5011	**1.5228**	1.5655	1.6184	1.8585
140	1.5011	**1.5209**	1.5612	1.5846	1.8018
150	1.5011	**1.5183**	1.5547	1.5930	1.7407
160	1.5011	**1.5170**	1.5460	1.5614	1.7313
170	1.5011	**1.5161**	1.5411	1.5502	1.6715
180	1.5011	**1.5154**	1.5402	1.5482	1.6071
190	1.5011	**1.5133**	1.5340	1.5466	1.5554
200	1.5011	**1.5103**	1.5265	1.5458	1.5446

D. *Comparison of methods for varying queue distribution*

In this subsection, we want to verify the capability of the proposed method for a different queue distribution. We set $Q \sim N(10, 4)$ with other parameters the same as (5). Table 4 shows the comparison of expected energy consumption among different methods. We can see from the table that the proposed method reduces energy consumption by 4.14% (Baseline_0) and 3.56% (average 21 baselines) and is 1.88% higher than the ideal consumption.

TABLE 4. E_{Exp} Comparison among Proposed, Baseline and Ideal Method for Gaussian Queue Distribution.

Method	Energy(10^6)	Method	Energy(10^6)
Ideal	1.5141	Baseline_{10}	1.5693
Proposed	**1.5431**	Baseline_{11}	1.5887
Baseline_0	1.6070	Baseline_{12}	1.5491
Baseline_1	1.5695	Baseline_{13}	1.5617
Baseline_2	1.5624	Baseline_{14}	1.5765
Baseline_3	1.5552	Baseline_{15}	1.5931
Baseline_4	1.5433	Baseline_{16}	1.6028
Baseline_5	1.5604	Baseline_{17}	1.6476
Baseline_6	1.5619	Baseline_{18}	1.6893
Baseline_7	1.5487	Baseline_{19}	1.7634
Baseline_8	1.5444	Baseline_{20}	1.8183
Baseline_9	1.5479		

IV. Conclusion and Future Work

This research proposes an adaptive strategy for connected eco-driving towards a pre-timed signalized intersection under uncertain traffic condition. The validation results indicate that the proposed 2-phase iterative approach can achieve an energy-efficient trajectory, given the information of SPaT and historical queue distribution. Numerical simulation results show that the proposed method can save an average of 8.88% energy consumption for uniform queue distribution and 3.56% for Gaussian queue distribution compared to baseline methods. The proposed method also works for varying radar range and different time the vehicle initially enters the DSRC range. In the future, more research will be conducted as listed below:

- Extend the adaptive eco-driving strategy to the intersections with actuated signals considering the dynamic uncertainty of SPaT information
- Develop an application programming interface (API) in VISSIM and implement the proposed model in microsimulation
- Conduct field test along the innovative corridor

V. Acknowledgment

This research is supported by The National Center for Sustainable Transportation (NCST).

References

[1] U.S. Environmental Protection Agency (EPA), “Fast Facts: U.S. Transportation Sector GHG Emissions 1990-2016”, [Online]. Available: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100USI5.pdf. [Accessed: Jan-2019].

[2] U.S. Department of Energy, “Transportation energy data book”, [Online]. Available: https://cta.ornl.gov/data/tedbfiles/Edition36_Full_Doc.pdf. [Accessed: Jan-2019].

[3] European Commission (EC), “eCoMove – Cooperative Mobility Systems and Services for Energy Efficiency”, [Online]. Available: http://www.ecomove-project.eu/. [Accessed: Jan-2019].

[4] U.S. Department of Transportation, “Applications for the Environment: Real-Time Information Synthesis (AERIS)”, [Online]. Available: https://www.its.dot.gov/research_archives/aeris/index.htm. [Accessed: Jan-2019].

[5] M. Li, K. Boriboonsomsin, G. Wu, W.-B. Zhang, and M. Barth, "Traffic energy and emission reductions at signalized intersections: a study of the benefits of advanced driver information," International Journal of Intelligent Transportation Systems Research, vol. 7(1), pp. 49-58, 2009.

[6] M. Barth, S. Mandava, K. Boriboonsomsin and H. Xia, "Dynamic ECO-driving for arterial corridors," *2011 IEEE Forum on Integrated and Sustainable Transportation Systems*, Vienna, 2011, pp. 182-188.

[7] P. Hao, G. Wu, K. Boriboonsomsin and M. J. Barth, "Eco-Approach and Departure (EAD) Application for Actuated Signals in Real-World Traffic," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 30-40, Jan. 2019.

[8] X. He, X. Liu, X. Liu, "Optimal vehicle speed trajectory on a signalized arterial with consideration of queue", *Transp. Res. C Emerg. Technol.*, vol. 61, pp. 106-120, Dec. 2015.

[9] F. Ye, P. Hao, X. Qi, G. Wu, K. Boriboonsomsin, M. Barth, "Prediction-based eco-approach and departure strategy in congested urban traffic", *Proc. 96th Annu. Meet. Transp. Res. Board*, 2017.