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Prediction-based Eco-Approach and Departure Strategy in Congested Urban Traffic

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ABSTRACT

Based on the Connected Vehicle (CV) technology, a number of Eco-Approach and Departure (EAD) strategies have been designed to guide vehicles to travel through signalized intersections in an eco-friendly way, avoiding unnecessary idling and minimizing acceleration/deceleration events. Most of the existing EAD applications were developed and tested in traffic-free scenarios or in a fully connected environment where presence and behavior of surrounding vehicles are detectable and predictable. In this study, we propose a prediction-based EAD strategy for more realistic scenarios, where there is a preceding vehicle, which can be either a connected or non-connected vehicle. Unlike in highway scenarios, predicting vehicle speed trajectory along signalized corridors is much more challenging due to the disturbances from signals, traffic queues and pedestrians. Based on vehicle activity data available via inter-vehicles communication or onboard sensing (e.g., by radar), we developed several artificial neural network (ANN)-based algorithms to perform short-term speed prediction of the preceding vehicle. Using signal phase and timing (SPaT) information and predicted state of the preceding vehicle, we improve the existing EAD algorithm to achieve better fuel economy and emissions reduction in the presence of preceding traffic and queues at intersections. Results from the numerical simulation show that the proposed prediction-based EAD strategy achieve 4.3% energy savings and 3.0%~28.6% air pollutant emission reduction compared to a conventional car following strategy.

Keywords: Preceding vehicles, Vehicle speed prediction, Prediction-based EAD, Emission estimation

I. INTRODUCTION

Our daily transportation activities not only consume a great amount of energy, but also produce a myriad of tailpipe emissions which contribute significantly to air pollution and global warming. For example, it is reported that transportation sector in the United States accounts for 27% of the total U.S. greenhouse gas (GHG) emissions, where surface vehicles (including light vehicles and medium/heavy duty trucks) play a dominant role [1][2]. The increasing worldwide concerns on these traffic-related socio-economic problems have driven a significant amount of research effort towards developing various environmentally sustainable strategies. Among others, eco-driving strategies such as vehicle speed limit control [3], fuel-efficient platooning [4], cooperative adaptive cruise control system [5], and eco-routing [6], are deemed to be cost-effective and potentially deployable in the near term. Besides, many eco-friendly applications and technologies have been well studied and highlighted in some major programs, such as the European Commission's ECOSTAND program [7] and the U.S. Department of Transportation's AERIS (Application for the Environment: Real-Time Information Synthesis) program [8]. One of the promising applications identified in the AERIS program is the Eco-Approach and Departure (EAD) application at signalized intersections, which takes full advantage of signal phase and timing (SPaT) and Geometric Intersection Description (GID) information via wireless communications to provide eco-friendly driving suggestions (e.g., speed profiles) as vehicles approach signalized intersections.

It is well known that vehicle fuel consumption and emissions are directly related to vehicle's speed trajectory [9]. Unlike driving on freeways, traffic streams on arterial roads can be interrupted by traffic signals. The frequent stop-and-go maneuvers in the arterial driving lead to excessive fuel consumption and GHG emissions [10]. Such effects are more prominent when vehicles approach the intersection in the red phase and have to decelerate from cruising speeds to full stops, idle to wait for the green phase, and then accelerate to depart from the intersection. Knowledge of SPaT information has been proven to be significantly effective in terms of improving fuel economy for arterial driving [9][11]. With the recent advances in Connected Vehicle (CV) technology, it is promising to develop advanced driving assistance systems (ADAS) such as EAD application to improve energy efficiency for traveling along signalized intersections. In [12], the authors adopted a Model Predictive Control (MPC) approach to obtain a sub-optimal cruise speed to achieve timely arrival at green lights, thus minimizing the idling time and stops at red phase along a signalized corridor. Another study utilized dynamic programming (A-star algorithm) to find the most fuel-efficient speed trajectory through a fixed time control signalized intersection [13]. A multi-stage optimal control approach was proposed in [14] adding the estimated queue dissipation time and location at the intersection as constraints. However, constraints from the preceding vehicle's speed trajectories were not considered. A series of EAD applications were designed in recent years for both fixed-time signals and actuated signals [11], [15-19]. However, to the best of our knowledge, the aforementioned studies either were conducted under traffic-free conditions or applied simple rules (e.g., keeping a safe distance) to passively handle the presence of preceding vehicles. Therefore, it would be beneficial for real-world deployment of EAD application to further explore the dynamic states from preceding vehicles and fuse this information into the trajectory planning process.

To this end, we propose a prediction-based EAD system which makes full use of activity information of preceding vehicles. Such information can be acquired via vehicle-to-vehicle (V2V) communication (if the preceding vehicle is a CV), onboard sensors (e.g., radar), or even infrastructure-based assistance (e.g., roadside camera). Based on the SPaT information and future states of the preceding vehicle predicted by artificial neural network (ANN)-based vehicle speed predictor(s), the improved EAD algorithm can provide an eco-friendly speed trajectory in the presence of preceding traffic and queues at intersections. Data from the Next Generation SIMulation (NGSIM) program [20] are used for model training and system performance evaluation. The remainder of this paper is organized as follows: Section II introduces some background information on existing EAD applications and state-of-the-art methods in time series prediction. Section III presents a detailed description of the prediction-based EAD system architecture and its components (e.g., ANN-based speed predictor), followed by a comparative numerical simulation study and result analyses in Section IV. The last section concludes the paper with further discussion.

II. BACKGROUND

A. Existing Eco-approach and departure (EAD) Applications

The EAD application was initially developed for fixed-timing signals whose phase sequence and duration are predetermined, and thus the advisory speed trajectory can be well defined with the available SPaT and GID information [15]. The EAD application for fixed-time signals has been shown to reduce fuel consumption and emissions by 10%-15% in microscopic simulation models [15] and by 13%-14% from real world testing [16]. An enhanced EAD application has shown satisfactory results for congested urban traffic conditions in a fully connected environment [17]. Extended efforts were made to develop an EAD application for actuated signals. In [18], the authors developed an EAD framework for actuated signals which uses the derived minimum and maximum times to next phase as principal SPaT information and considers the dynamics (e.g., relative speed and distance from radar detection) of the preceding vehicle (along the same lane). Numerical analysis showed significant benefits in terms of fuel savings and GHG emissions reduction, especially for roadway segments with relatively low speed limit (less than or equal to 30 mph).

Most of the existing EAD studies focused on the interaction between the subject vehicle and the traffic signals. Those applications work well under light traffic conditions, but not effective in congested traffic, especially when there are preceding vehicles or queues. Figure 1 shows a rule-based strategy to deal with preceding vehicles. When there is no preceding vehicle ahead (within the detection range) in the same lane, the target speed estimated from the EAD algorithm is then displayed on the artificial dashboard. When radar detects a preceding vehicle in the near front, the display of target speed is turned off to avoid any distraction. With such a heuristic strategy, the EAD application may not work effectively in congested urban traffic, especially when there is often a preceding vehicle within the detection range. To address this issue, we need to consider both preceding traffic and signal information in the EAD application development in order to achieve desired system performance even under congested traffic conditions.

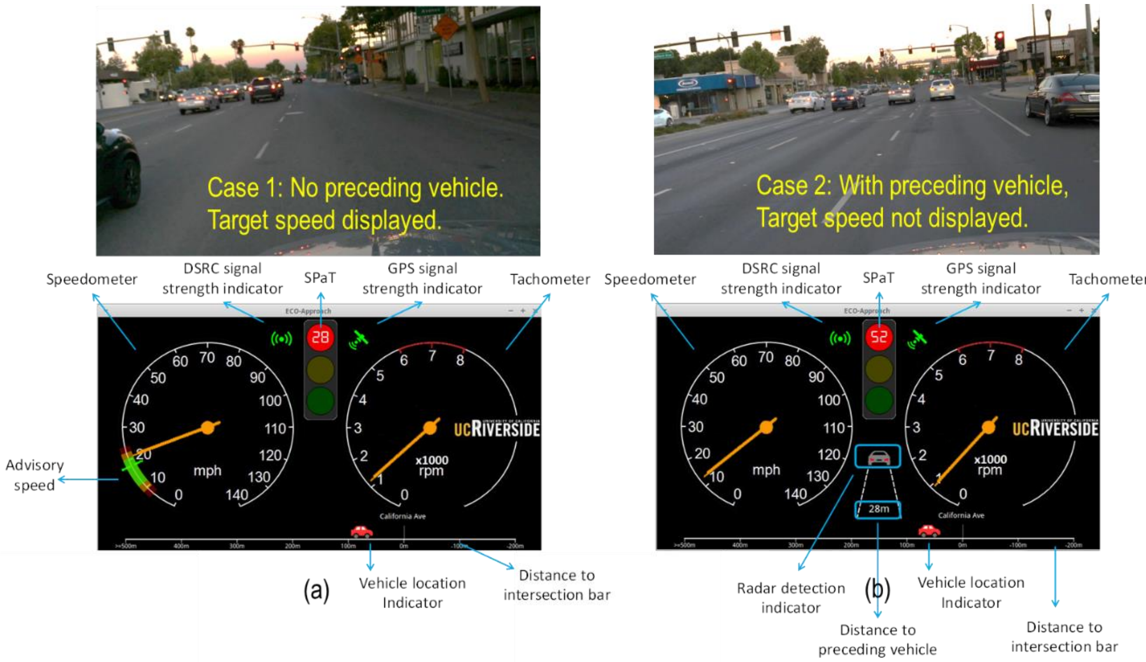


FIGURE 1 Speed profile for non-adjusted profile and adjusted profile (Source: [19])

B. Car-following Models

At the core of a microscopic traffic simulation model, the car-following model governs the vehicle behaviors when following a preceding vehicle in traffic. In the past decades, a variety of car-following models have been proposed and studied [21-22]. For example, the optimal velocity model [23] and the full velocity difference model [24] were proposed based on the intuitive vehicle speed changing. The well-known Gipps' model [25] and the intelligent driver model (IDM) [26] were proposed with emphasis on driver's acceleration and deceleration strategies. More recently, to identify the cause and formation of the stop-and-go traffic oscillations, Laval et al [27] incorporated non-equilibrium driver behavior into Newell's simplified car-following model [28]. Traffic oscillations captured by [29] use a desired acceleration model with a white-noise term. It showed that small driver errors can result in the stop-and-go oscillation. Comparative studies between major car-following models can be found in [30]. In this work, the Gipps' model is adopted as the baseline driving behavior in the microscopic traffic simulation tool.

C. State-of-the-art Approaches for Vehicle Movement Prediction

Accurate and reliable prediction of vehicle speed trajectory is an important component in many Intelligent Transportation Systems (ITS) applications, particularly for safety and environmental related applications. It is a challenging task as the vehicle speed trajectory may be affected by many factors, e.g. signal status, surrounding vehicles' maneuver. In the literature, various approaches for vehicle speed prediction have been investigated and evaluated. In general, the existing vehicle speed prediction strategies can be categorized into two major classes: model-based approaches and data-driven approaches. The model-based approaches predict the vehicle speed trajectory based on pre-defined model structures such as Constant Speed Model (CS), Constant Acceleration Model (CA), Constant Yaw Rate and Acceleration Model (CYRA). A comparison of these different models in applications of target tracking was conducted in [31] which indicates that

CYRA is superior to others for vehicle trajectory prediction. However, the underlying dynamics of human cognition, decision making and execution of drivers and vehicle systems are extremely complex and these simplified models may not be applicable [32]. On the other hand, data-driven approaches are recently well investigated since they show more flexibility and applicability in representing system dynamics. Good examples of effective data-driven approaches for vehicle speed trajectory prediction include Non-Parametric Regression (NPR), Gaussian Mixture Regression (GMR) and Artificial Neural Networks (ANNs) [33-35]. In [33], the defined maneuver recognition algorithm selected the best vehicle trajectory that minimizing a cost function by comparing the current maneuver to the pre-defined trajectory set. However, this maneuver recognition-based prediction has some limitation in applying for vehicle movement prediction in a signalized intersection. The road structure and driving behaviors in the signalized arterials are much more complex compared to highways segments, resulting in high dimensional vehicle trajectory structure. Considering the requirement for large sampled vehicle trajectories and complexity of maneuver recognition in large time series datasets, it is challenging to apply maneuver recognition approach to vehicle movement prediction in the real world urban traffic. Gaussian Mixture Regression (GMR) is another promising parametric method to approximate or predict vehicle trajectories by calculating a conditional probability density function that consists of a weighted linear combination of Gaussian component densities [34]. Since the Gaussian Mixture Regression (GMR) method is applicable under the assumption of jointly Gaussian distribution of input and output datasets, it may result in huge deviation if the assumption does not hold. Artificial Neural Networks (ANNs) have been proven to be an effective method for accurately forecasting vehicle speed, and position. It is necessary and beneficial for designing safe and fuel/energy efficient eco-driving applications [35]. The strong capability of capturing the complex and nonlinear dynamics makes ANNs a popular approach in prediction problems. A comparative study of major parametric and non-parametric approaches for vehicle speed prediction on highways indicates that ANNs outperform all the other methods in terms of both predictive accuracy and applicability [35].

III. PREDICTION-BASED ECO-APPROACH AND DEPARTURE STRATEGY

A. System Architecture

In this work, we aim to develop an enhanced EAD application that is applicable in relatively congested urban traffic. The overall architecture of the proposed Prediction-based EAD application is shown in Figure 2. The proposed system acquires various information from multiple data resources: SPaT and GID information from DSRC-equipped signal controller at the intersection, subject vehicle dynamics from on-board diagnostics (OBD) port, subject vehicle positions from on-board GPS receiver and activity data of preceding vehicle either from V2V communication if it is an DSRC-equipped vehicle or from on-board radar detection if it is an unequipped vehicle. A vehicle trajectory planning algorithm is developed to provide an eco-friendly speed trajectory in both light traffic and relatively congested traffic conditions based on the above acquired information and reliable prediction of preceding vehicle's future states. Human-Machine Interface (HMI) is designed to inform driver a number of items such as vehicle's current speed, vehicle's Revolutions Per Minute (RPM), SPaT information, vehicle's distance to intersection and the target speed calculated from the Enhanced Vehicle Trajectory Planning Algorithm (EVTPA) with the consideration of preceding traffic. As what we highlighted in the flow chart, predicting preceding vehicle's future state and design an eco-friendly trajectory according to that is the key contribution of this paper.

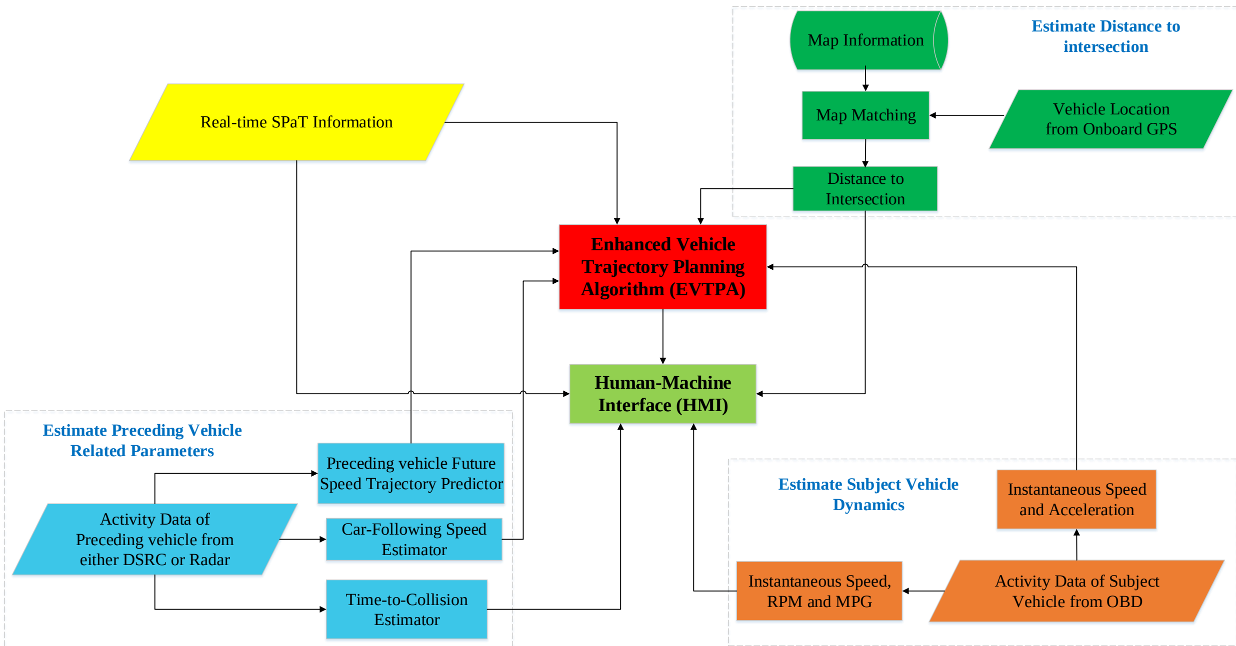


FIGURE 2 Prediction-based EAD system architecture

B. Artificial Neural Network (ANN)-based Vehicle Speed Prediction

A reliable and accurate prediction on preceding vehicle's future state is essential for applying EAD strategy in congested urban traffic conditions. As aforementioned, a number of studies have evaluated various time series prediction approaches for predicting vehicles' speeds under the highway scenarios. However, to the best of our knowledge, none of them have discussed the prediction performance for urban driving. The prediction of vehicle speed trajectory along the signalized corridors is much more challenging due to the disturbances from signals, traffic queues and pedestrians.

In this study, we implement a radial basis function neural network (RBF-NN) [36] for arterial driving under three different scenarios. ANN-based vehicle speed predictor has a basic input-output structure as shown in Figure 3. The network input is the historical preceding vehicle speed trajectory and the output is predicted future speed trajectory.

The implemented RBF-NN is a two-layer feed-forward networks with K hidden nodes. A radial basis function needs to be predefined for each hidden node to activate neurons in the hidden layer. Each hidden node contains a nonlinear activation function. Here, we chose the Gaussian function as the activation function for the RBF-NN, formulated as:

$$\varphi_{j\_m} = \exp\left[-\left(S_{j\_m} - \mu_j\right)^T \Sigma_j^{-1} \left(S_{j\_m} - \mu_j\right)\right] \tag{1}$$

$$S_{j\_m} = \sum_{i=0}^{n} w_{ij\_x} x_i + b_{ij} \tag{2}$$

where φ_{j_m} is the activated response of node m in layer j; x_i is the activation of a particular node i in the prior layer; S_{j_m} is the accumulator output of all the relevant nodes in the prior layer with their corresponding weights; w_{ij} is the set of input weights for node x; and b_{ij} is the constant bias; μ_j and Σ_j are the mean and covariance matrix of the j^{th} Gaussian function. The mean μ_j represents the center and Σ_j indicates the shape of the activation function. Finally, the output of each node at the RBF-NN's output layer is computed as a linear combination of the outputs of the hidden nodes.

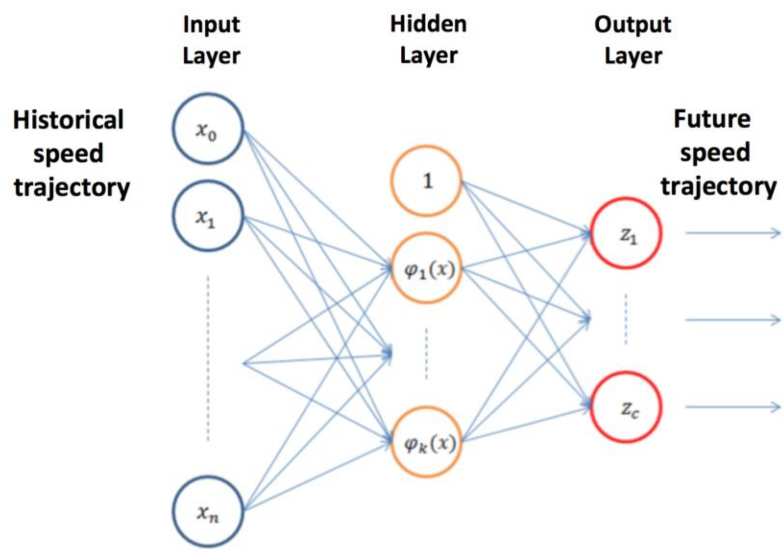


FIGURE 3 ANN-based vehicle speed predictor structure

C. Trajectory Planning Algorithm with Consideration of Preceding Traffic

An enhanced vehicle trajectory planning algorithm (EVTPA) is developed to address the situation where there exist mixed connected and conventional preceding vehicles. Two situations are considered in designing the desired trajectory for the subject vehicle in terms of both safety and energy/fuel economy. If the vehicle is approaching the intersection during the red phase, the SPaT information and estimated preceding queue end location are utilized to design the optimal trajectory to avoid unnecessary idling and acceleration/deceleration. Otherwise, we apply Gipps' model to develop a trajectory that is safe and energy-efficient. The proposed EVTPA is illustrated by the overall block diagram in Figure 4. When the proposed EAD system is triggered in relatively congested urban traffic, location of the end of queue with respect to the subject vehicle is estimated based on the predicted preceding vehicle trajectories. A virtual stop line is defined as a buffer space (i.e. length of vehicle) behind the preceding queue end. The EAD trajectory planner takes the delay caused by the preceding queue and distance to the estimated virtual stop line as the inputs to generate a trajectory that minimizing the fuel consumption and emission. At each time step, the vehicle trajectory planning algorithm also predict the time to collision based on the preceding vehicle's movement to guarantee safety in our planed maneuver. If the subject vehicle will be under the risk of collision in the near future, car following mode will take over to guide the driver through the intersection while keep safety distance from the preceding vehicle. The transitions between EAD trajectory planner and car following mode enable the proposed EVTPA to maximize fuel savings and environmental benefits without compromising the safety. We refer interested readers to [9] about any detail in basic EAD velocity planning algorithm.

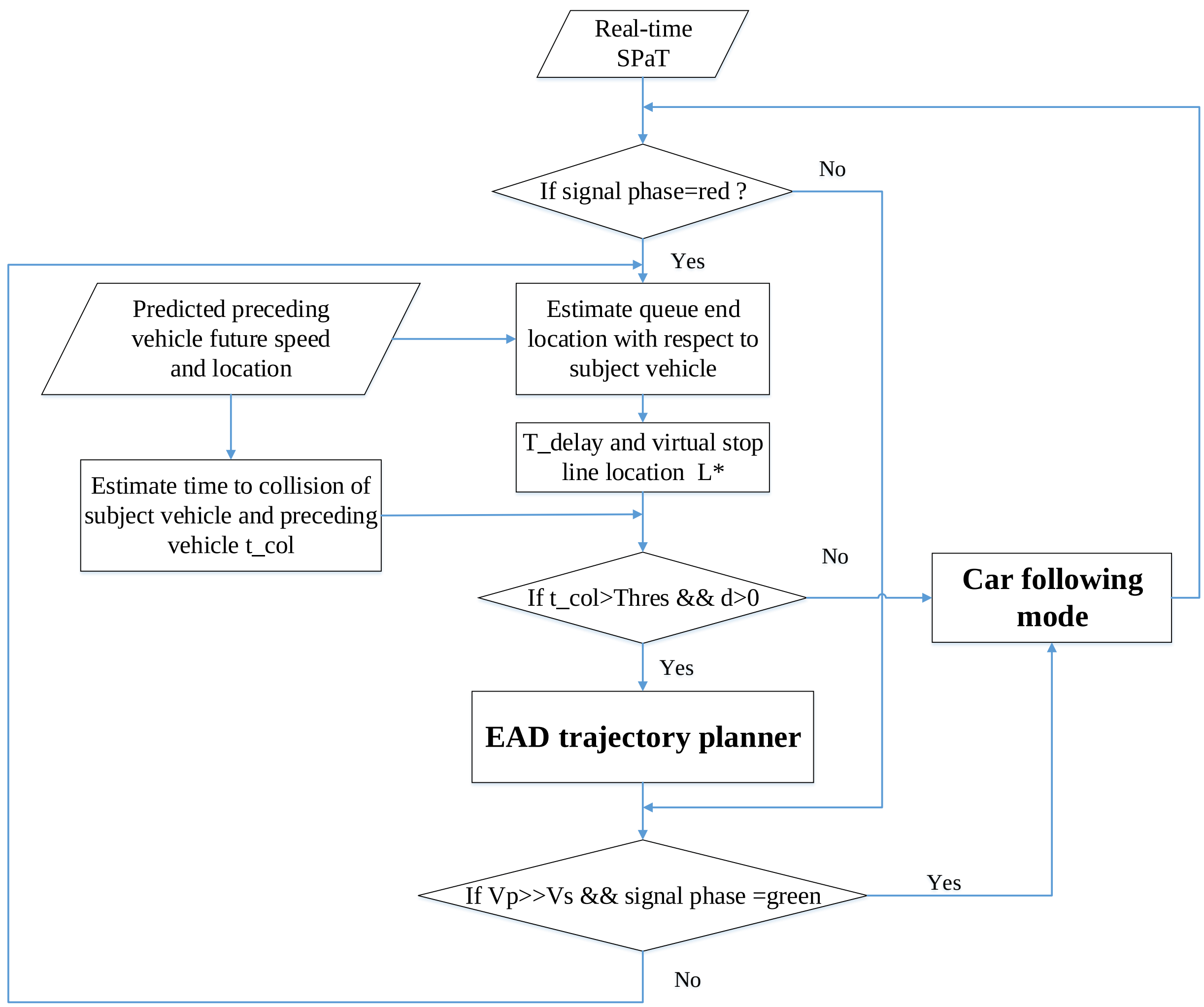


FIGURE 4 Block diagram of enhanced vehicle trajectory planning algorithm

IV. RESULTS AND DISCUSSION

A. Data Descriptions

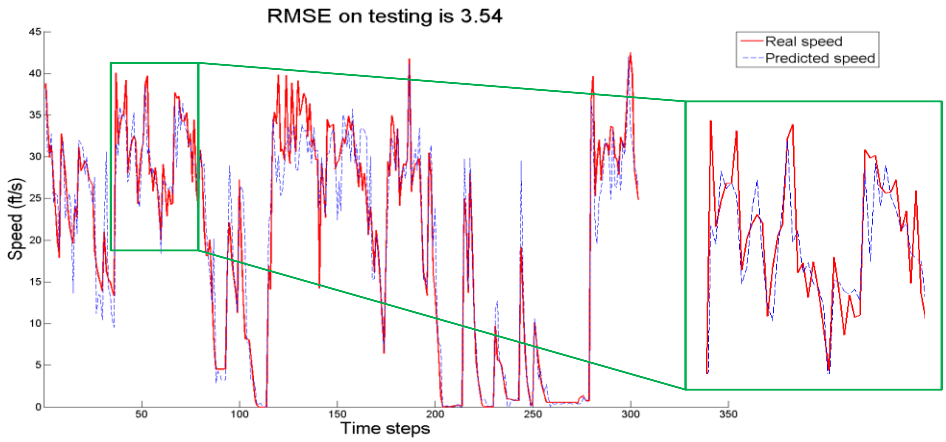
The Next Generation SIMulation community (NGSIM) data collected from an arterial segment on Peachtree in Atlanta, GA are used for training and testing the ANN-based vehicle speed predictors. The NGSIM Peachtree datasets include the spatial and temporal information of all the vehicles as well as the traffic light information of four signalized intersections within the arterial segment from two periods: 12:45 p.m. to 1:00 p.m., and 4:00 p.m. to 4:45 p.m. [20]. We utilized 4:00 p.m. to 4:45 p.m. period data for training and 12:45 p.m. to 1:00 p.m. period data for testing. The SPaT information in both datasets are accessible for index reference. To develop accurate and reliable prediction of vehicle speed trajectory, we extract speed trajectory of each individual vehicle from both datasets by vehicle ID. Then, we utilized a sliding window to partition the time series dataset into a number of segment pairs with finite lengths. For each pair of segments, one is the past segment and the other is the future segment. This enables us to utilize the historical speed trajectory to predict the future speed trajectory within a pre-defined prediction horizon. In addition, the traffic signal status and distance to the stop-bar jointly effect the driver behavior when approaching a signalized intersection. Therefore, we divide the whole vehicle speed trajectories into three subgroups based on different driving situation. In Situation 1, the vehicle is still far away from the stop-bar and current phase is red; In Situation 2, the vehicle is close to the stop-bar but current phase is still red; In Situation 3, the current phase is green. The classified vehicle speed trajectories are used for developing and evaluating ANN-based vehicle speed predictors in each scenario, respectively.

B. Evaluating the Performance of ANN-based Vehicle Speed Predictors

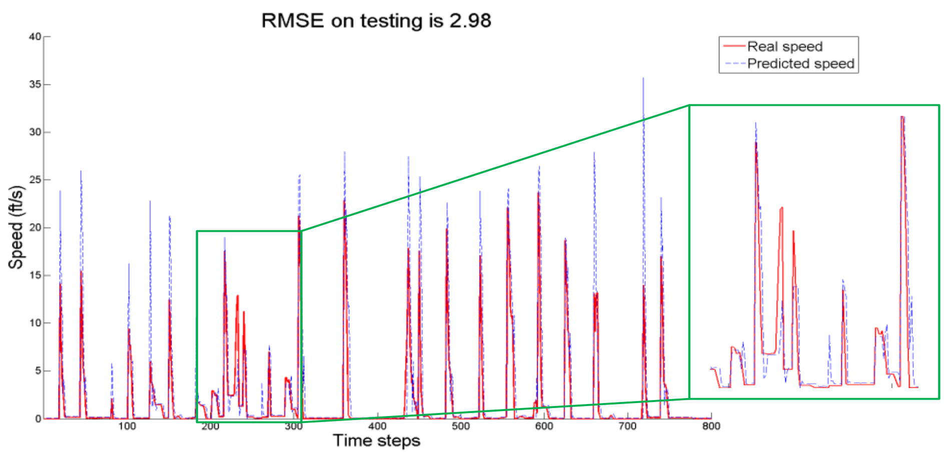
We first analyze the performance of developed ANN-based vehicle speed predictors based on real world driving data in urban traffic (NGSIM Peachtree data). To better forecast speed trajectories for vehicle driving through signalized corridors, current signal phase and vehicle's distance to the signalized intersection as two major influential factors are utilized to partition the time series data into three subgroups with different driving conditions. ANN-based speed The Root Mean Square Error (RMSE) is adopted in this study to measure the time series forecasting accuracy, defined as

$$RMSE = \sqrt{\sum_{N} (y - \hat{y})^2 / N} \tag{3}$$

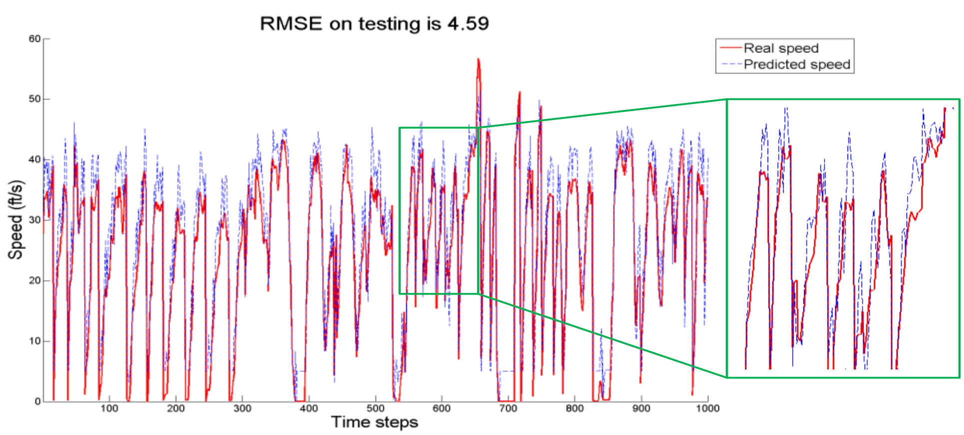
where N is the number of measurements, y and $\hat{y}$ indicate the actual value and predicted value, respectively. RMSEs of the predicted vehicle speed trajectories with respect to the ground truth under three driving conditions are 3.54 ft/s, 2.98 ft/s and 4.59 ft/s, respectively. Figure 5 illustrates the predicted speed from the developed ANN-based predictor vs. the actual speed with prediction horizon of 3 seconds under three driving scenarios, respectively. The selected horizon length of 3 sec for predicting vehicle's speed seems to be an acceptable choice. As shown in Figure 5, the developed ANN-based vehicle speed predictor is able to provide reliable results with satisfying prediction accuracy for each driving condition.



(a) Condition 1: Red signal phase; Distance to intersection> predefined threshold



(b) Condition 2: Red signal phase; Distance to intersection<predefined threshold



(c) Condition 3: Green signal phase

FIGURE 5 Results of vehicle speed prediction under different driving conditions

C. Validation of the Trajectory Planning Algorithm with Traffic

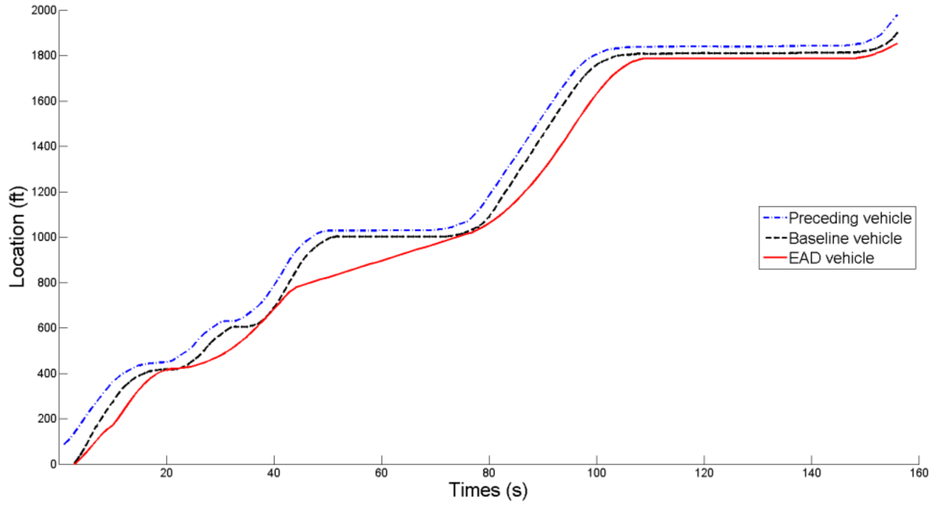
Based on NGSIM Peachtree data, we take each northbound through movement vehicles as preceding vehicles (185 vehicles in total), and create an imaginary subject vehicle that is following that preceding vehicle. As the preceding vehicle trajectories are generated from vehicle's driving information in NGSIM, they are utilized as the input for the proposed prediction method, and the criterion for a safety check, i.e. if any trajectory of the following vehicle comes too close to that of the preceding vehicle, the trajectory planned algorithm is not reliable on safety. We also generate the baseline vehicle trajectories that follow Gipps' car following model in simulation for comparison.

Figure 6 uses the trajectory of three example vehicles to illustrate how the proposed EAD system reduces unnecessary idle time and speed oscillation, while keeping a safe distance from the preceding vehicle when driving through signalized corridors. We show a representative trajectories of preceding vehicle, baseline vehicle and EAD equipped vehicle through signalized corridors by blue, black and red curves respectively.

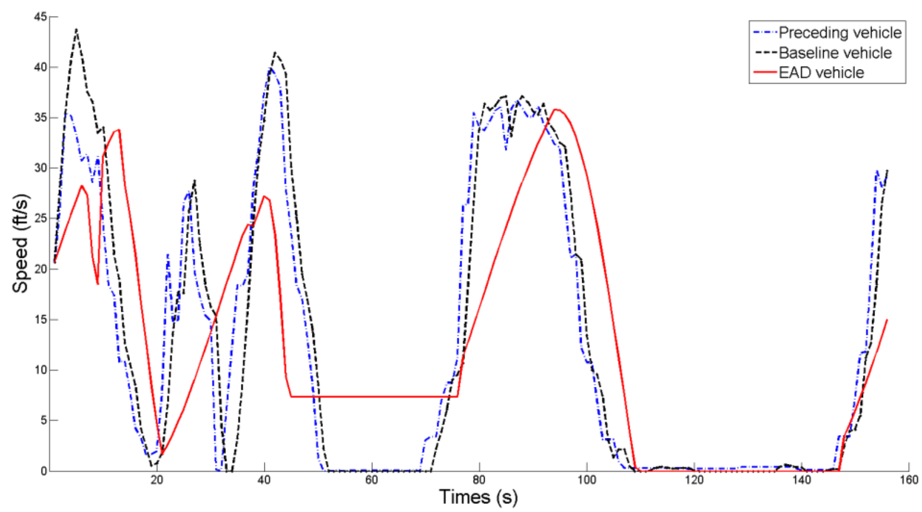
In Figure 7, we show the speed distribution for the total 185 trajectories of EAD equipped vehicles and baseline vehicles respectively. We observe a significant drop on the percentage of idling or near idling situations (speed between 0 ~ 5 ft/s) for vehicles with the assistance of EAD system compared to baseline vehicles. Meanwhile, the percentage of vehicles driving in high speed (i.e. speed larger than 40 ft/s) is significantly reduced. Those findings imply the proposed EAD system is able to avoid unnecessary idling, accelerations and decelerations even in congested urban traffic.

To quantify the effectiveness of the proposed EAD system in terms of energy savings and emissions reduction, the U.S. Environmental Protection Agency's MOtor Vehicle Emission Simulator (MOVES) model [37] is applied to estimate the associated energy consumption and emissions. MOVES is a state-of-the-art on-road emission modeling system that uses Vehicle Specific Power (VSP) as its primary metric. The second-by-second Vehicle Specific Power (VSP) can firstly be calculated based on vehicle's speed trajectory and road grade information. Then, the operating mode (OpMode) distribution over 23 bins for running exhaust emissions can be derived from a mapping of VSP, speed and acceleration values. Finally, with the OpMode distribution, we are able to estimate the energy consumption and emissions of all the vehicle trajectories based on the emission factors from MOVES database.

Table 2 shows the energy and environmental benefits of the proposed prediction-based EAD system. We compare the overall performance of the vehicles that equipped with EAD system and baseline vehicles that follow Gipps' model in terms of energy savings and emissions reduction. Total 4.5% energy savings are achieved by applying the proposed EAD system compared to traditional car following method. Also, we observed significant reduction in air pollutant emissions of the EAD-equipped vehicle. The emissions of HC, CO, NO_X, CO_2 and $PM_{2.5}$ per mile in the EAD-equipped vehicles are 3.0%, 11.8%, 30.6%, 4.3%, 4.3% and 28.6% less, respectively.

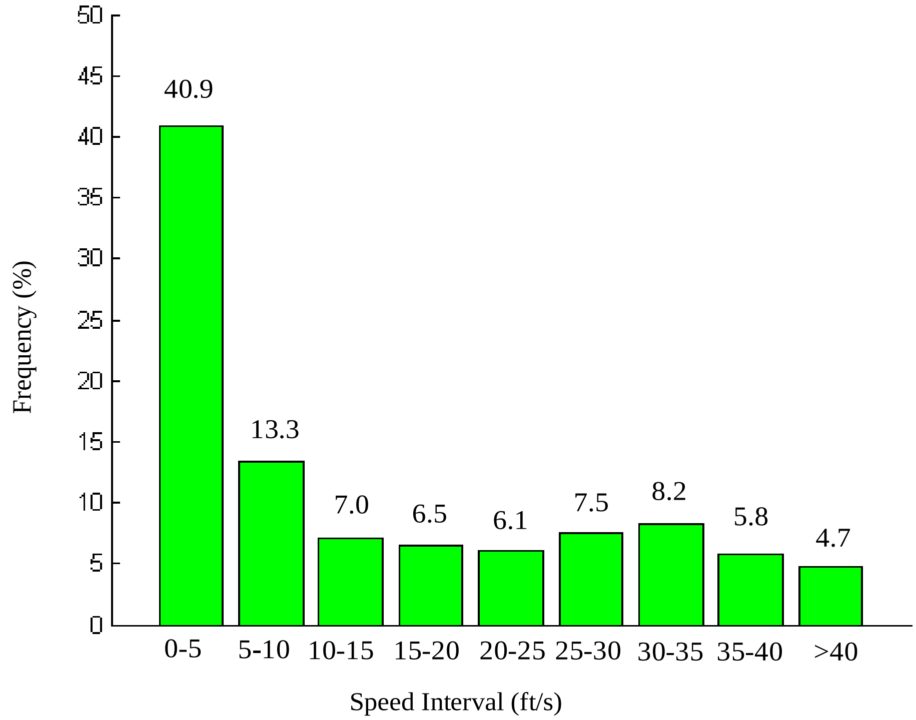


(a) Time-space trajectories

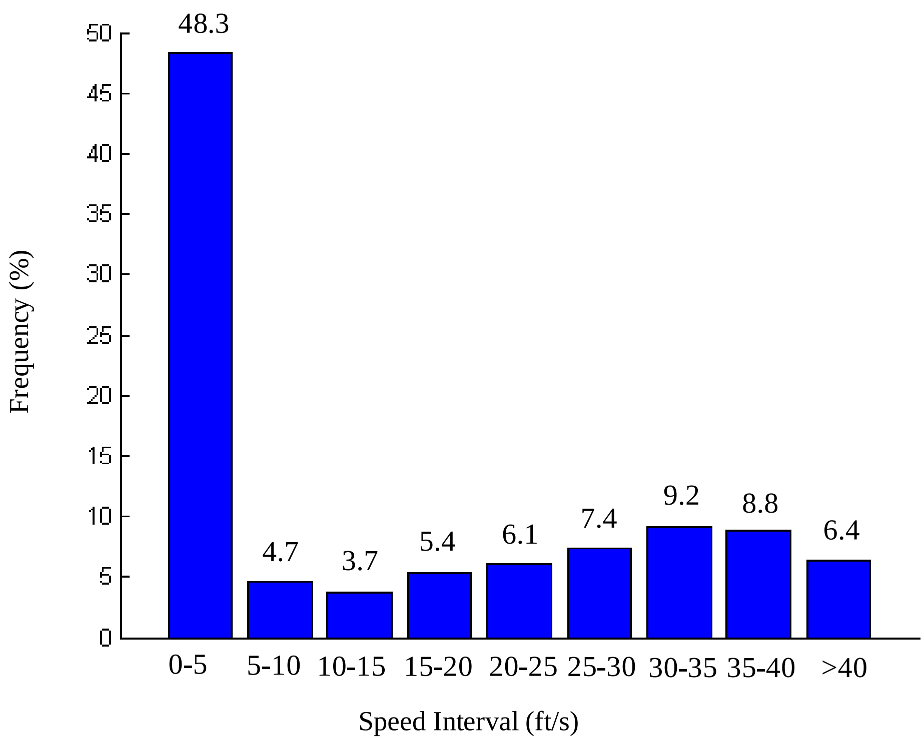


(b) Speed profiles

FIGURE 6 A comparison of different driving strategies.



(a) Speed distribution for EAD equipped vehicles



(b) Speed distribution for baseline vehicles

FIGURE 7 Impact of proposed EAD system on vehicle speed distribution

TABLE 1 Performance of the proposed prediction-based EAD algorithm

Vehicle	HC (g/mile)	CO (g/mile)	NO_X (g/mile)	CO_2 (g/mile)	Energy (KJ/mile)	PM2.5 (mg/mile)
Preceding vehicle	0.49	8.27	1.24	773	10767	21.9
Baseline vehicle	0.44	7.61	1.10	694	9662	19.5
EAD vehicle	0.42	6.71	0.76	664	9245	13.9
Saving in %	3.0	11.8	30.6	4.3	4.3	28.6

V. CONCLUSIONS

This research proposes a prediction-based EAD system that enables the driver to travel through a signalized intersection in a safe and eco-friendly manner in congested urban traffic. The validation results indicate that the proposed ANN-based predictor can predict preceding vehicle's speed trajectory with reasonable accuracy under different scenarios. Based on SPaT and GID information as well as predicted states of preceding vehicle, the proposed EAD algorithm can provide a smoothed and energy-efficient trajectory, considering the preceding traffic and possibly queues at intersections. Numerical simulation results show that the proposed system is able to save 4.5% of energy and reduce air pollutant emissions by 3.1%~30.6% compared to conventional vehicles (simulated by Gipps' car-following model). In the future, more research will be conducted based under the proposed framework.

(1) We will upgrade the proposed EAD system into an automated, longitudinally-controlled system. It is expected that better system performance and more environmental benefits can be achieved as the vehicle automation is able to mitigate the negative impacts due to manual driving (e.g., distraction).

(2) We will conduct sensitivity analysis on the prediction time horizons to find the most reasonable prediction time length. In addition, the computation time and robustness of the trajectory prediction method will be further investigated.

(3) We plan to implement the proposed EAD system in a test vehicle and conduct a field operational test to further evaluate performances of the algorithm.

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REFERENCES

1. U.S. Environmental Protection Agency (EPA), National greenhouse gas emissions data report, 2013
2. U.S. Department of Energy, Transportation energy data book, Table 2.5, 2014.
3. Yang, H., Jin, W.-L., "A control theoretic formulation of green driving strategies based on inter-vehicle communications," Transportation Research Part C: Emerging Technologies 41, pp. 48–60, 2014
4. A. Al Alam, A. Gattami, and K. H. Johansson, "An experimental study on the fuel reduction potential of heavy duty vehicle platooning," in Proc. 13th Int. IEEE Conf. Intell. Transp. Syst., pp. 306–311, Sep. 2010
5. B. Asadi, A. Vahidi, "Predictive Cruise Control: Utilizing Upcoming Traffic Signal Information for Improving Fuel Economy and Reducing Trip Time", Trancactions on IEEE Control Systems Technology, April 26, 2010
6. Sun, J., Liu, H.X., "Stochastic eco-routing in a signalized traffic network". Transp. Res. Part C: Emerg. Technol. 59, pp. 32–47, 2015
7. Canaud, M., El Faouzi, N.E.: 'ECOSTAND: towards a standard methodology for environmental evaluation of ITS', Transp. Res. Procedia, 6, pp. 377–390, 2015
8. U.S. Department of Transportation, "Applications for the Environment: Real-Time Information Synthesis (AERIS)", http://www.its.dot.gov/aeris/. Accessed on August 7th, 2015
9. Matthew Barth, Sindhura Mandava, Kanok Boriboonsomsin, Haitao Xia, "Dynamic ECO-Driving for Arterial Corridors", IEEE Forum on Integrated and Sustainable Transportation Systems, Vienna, Austria, June, 2011
10. Li, X., Cui, J., An, S., Parsafard, M., "Stop-and-go traffic analysis: Theoretical properties, environmental impacts and oscillation mitigation", Transportation Research Part B: Methodological 70, pp. 319–339, 2014
11. H. Xia, K. Boriboonsomsin, M. Barth, "Dynamic Eco-Driving for Signalized Arterial Corridors and Its Indirect Network-Wide Energy/Emissions Benefits", Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, 17(1), pp. 31 – 41,2013
12. Asadi B, Vahidi A. "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time", IEEE Transactions on Control Systems Technology 19(3):707–714, 2011
13. R. K. Kamalanathsharma, and H. Rakha, "Agent-based modeling of Eco-Cooperative Adaptive Cruise Control System in the Vicinity of Intersection," Intelligent Transportation Systems (ITSC), 15th International IEEE Conference, pp. 840-845, 2012
14. He, X., Liu, H.X., Liu, X., "Optimal vehicle speed trajectory on a signalized arterial with consideration of queue", Transport. Res. Part C: Emer. Technol. 61, pp.106–120, 2015
15. H. Xia, K. Boriboonsomsin, M. Barth, "Dynamic Eco-Driving for Signalized Arterial Corridors and Its Indirect Network-Wide Energy/Emissions Benefits", Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, 17(1), pp. 31 – 41,2013
16. H. Xia, K. Boriboonsomsin, F. Schweizer, A. Winckler, K. Zhou, WB. Zhang, M. Barth, "Field Operational Testing of ECO-Approach Technology at a Fixed-Time Signalized Intersection", 15th International IEEE Conference, Intelligent

Transportation Systems Conference (ITSC), pp. 188-193, Sep. 2012

17. H. Xia, G. Wu, K. Boriboonsomsin, M. Barth, “Development and Evaluation of an Enhanced Eco-Approach Traffic Signal Application for Connected Vehicles”, The 16th IEEE Conference on Intelligent Transportation Systems (ITSC), The Hague, Netherlands, October 6 – 9, 2013
18. P. Hao, G. Wu, K. Boriboonsomsin, M. Barth. “Developing a Framework of Eco-Approach and Departure Application for Actuated Signal Control”. IEEE on Intelligent Vehicles Symposium, Seoul, Korea. June 28 – July 1, 2015
19. P. Hao, G. Wu, K. Boriboonsomsin, M. Barth. “Eco-Approach and Departure (EAD) Application for Actuated Signal in Real-world Traffic”, submitted to Transportation Research Board (TRB) 96th Annual Meeting for presentation, Washington D.C, Jan. 8-12, 2017
20. US Department of Transportation, “NGSIM – Next Generation Simulation,” http://www.ngsim.fhwa.dot.gov – Access date: May 5, 2007.
21. Pipes, L., “An operational analysis of traffic dynamics”, Journal of Applied Physics 24, pp.274–281, 1953
22. Chandler, R., Herman, R., Montroll, E., “Traffic dynamics: studies in car following”, Operations research, 1–17, 1958
23. Bando, M., Hasebe, K., Nakayama, A., “Dynamical model of traffic congestion and numerical simulation”, Physical Review E, 51, pp. 1035–1042, 1995
24. Jiang, R., Wu, Q., Zhu, Z., “Full velocity difference model for a car-following theory”, Physical Review E 64, 017101, 2001.
25. Gipps, P., “A behavioural car-following model for computer simulation”, Transportation Research Part B 15, pp.105–111, 1981
26. Treiber, M., Hennecke, A., Helbing, D., “Derivation, properties, and simulation of a gas-kinetic-based, non-local traffic model”, Physical Review E 59, pp. 239–253, 1999
27. Laval, J., Leclercq, L., “A mechanism to describe the formation and propagation of stop-and-go waves in congested freeway traffic”, Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences 368, pp. 4519–4541, 2010
28. Newell, G., “A simplified car-following theory: a lower order model”, Transportation Research Part B 36, pp. 195–205, 2002
29. Laval, J., Toth, C.S., Zhou, Y., “A parsimonious model for the formation of oscillations in car-following models”, Transportation Research Part B 70, pp. 228–238, 2014
30. Treiber, M., Kesting, A., “Traffic Flow Dynamics: Data, Models and Simulation”. Springer, 2013b
31. R. Schubert, E. Richter, and G. Wanielik, “Comparison and evaluation of advanced motion models for vehicle tracking,” International Conference on Information Fusion, Cologne, Germany, Jul. 2008
32. S. Lefevre, C. Sun, R. Bajcsy, and C. Laugier, “Comparison of parametric and non-parametric approaches for vehicle speed prediction,” in Proc. Amer. Control Conf. (ACC), pp. 3494–3499, Jun. 2014
33. A. Houenou et. al, “Vehicle Trajectory Prediction based on Motion Model and Maneuver Recognition.” Japon, IEEE-IROS, 2013
34. J. Wiest, M. Hoffken, U. Kresel, and K. Dietmayer, “Probabilistic trajectory prediction with Gaussian mixture models,” in Proc. IEEE IV Symp., pp. 141–146,

Jun. 2012

35. J. Park, D. Li, Y. Murphey, J. Kristinsson, R. McGee, M. Kuang, and T. Phillips, "Real time vehicle speed prediction using a neural network traffic model," in Proc. IJCNN, pp. 2991–2996, 2011
36. S. Elanayar and Y. C. Shin, "Radial basis function neural network for approximation and estimation of nonlinear stochastic dynamic systems," IEEE Trans. Neural Networks, vol. 5, pp. 594–603, 1994
37. U.S. Environmental Protection Agency, "Motor Vehicle Emission Simulator", http://www.epa.gov/otaq/models/moves/. Accessed on Nov 20th, 2014