Title
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Journal
IEEE Transactions on Intelligent Transportation Systems, 20(4)

ISSN
1524-9050 1558-0016

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Publication Date
2018-09-13

DOI
10.1109/TITS.2018.2856809

Peer reviewed

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Article *in* IEEE Transactions on Intelligent Transportation Systems · September 2018

DOI: 10.1109/TITS.2018.2856809

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Prediction-based Eco-Approach and Departure at Signalized Intersections with Speed Forecasting on Preceding Vehicles

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***Abstract*— Using Connected Vehicle (CV) technology, a number of Eco-Approach and Departure (EAD) strategies have been designed to guide vehicles through signalized intersections in an eco-friendly way. Most of the existing EAD applications have been developed and tested in traffic-free scenarios or in a fully connected environment where the presence and behavior of all surrounding vehicles are detectable. In this study, we describe a *prediction-based* EAD strategy that can be applied towards more realistic scenarios, where the surrounding vehicles can be either a connected or non-connected. Unlike highway scenarios, predicting speed trajectories along signalized corridors is much more challenging due to disturbances from signals, traffic queues and pedestrians. Based on vehicle activity data available via inter-vehicle communication or onboard sensing (e.g., by radar), we evaluate three state-of-the-art nonlinear regression models to perform short-term speed forecasting of the preceding vehicle. It turns out Radial Basis Function Neural Network (RBF-NN) outperformed both Gaussian process (GP) and Multi-Layer Perceptron network (MLP-NN) in terms of prediction accuracy and computational efficiency. Using signal phase and timing (SPaT) information and the predicted state of the preceding vehicle, our *prediction-based* EAD algorithm achieved better fuel economy and emissions reduction in urban traffic and queues at intersections. Results from the numerical simulation using the Next Generation SIMulation (NGSIM) dataset show that the proposed *prediction-based* EAD system achieve 4.0% energy savings and 4.0% - 41.7% pollutant emission reduction compared to a conventional car following strategy. Prediction-based EAD saves 1.9% energy and reduces criteria pollutant emissions by 1.9% - 33.4% compared to an existing EAD algorithm without prediction in urban traffic.**

***Index Terms*— Vehicle speed forecasting, Preceding traffic constraints, Eco-approach and departure, Energy Consumption, Criteria pollutant emissions reduction**

I. Introduction

OUR daily transportation activities not only consume a great amount of energy, but also produce tailpipe emissions that contribute significantly to air pollution and global warming. For example, it is reported that transportation sector in the United States accounts for approximately 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 these, eco-driving strategies such as vehicle speed limit control [3], fuel-efficient platooning [4], cooperative adaptive cruise control systems [5], and eco-routing [6], are deemed to be cost-effective and potentially deployable in the near term. In addition, many eco-friendly applications and technologies have been well studied and highlighted in major research 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 developed in the AERIS program is the Eco-Approach and Departure (EAD) 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 a 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 and associated accelerations in the arterial driving lead to excessive fuel consumption and GHG emissions. Such effects are more prominent when a vehicle approaches an intersection during a red phase and has to decelerate from cruising speed to a full stop, 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 - 10]. 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. Asadi et al. [5] 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

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signalized intersection [11]. A multi-stage optimal control approach in [12] adds the estimated queue dissipation time and location at the intersection as constraints. Yang et al. [13] developed an ECO-CACC algorithm with considering queue effect to minimize the fuel consumption when vehicles proceed through signalized intersections. In [14], authors incorporated individual driver characteristics into the design of advanced driver assistance system for signalized intersections.

A series of EAD applications were designed in recent years for both fixed-time signals and actuated signals [10], [15 - 18]. However, the aforementioned studies were applied and conducted real world experiments in traffic-free condition. Therefore, when considering the real-world deployment of the EAD application, it is beneficial to further explore the dynamic states from preceding vehicles and incorporate it into trajectory planning process. Forecasting vehicle speed trajectory in urban arterial is a challenge task as the vehicle's maneuvers may be affected by various dynamic factors, e.g. signal status, traffic, driver's experience, weather and etc. A number of recent effort has been made to incorporate the vehicle speed prediction to achieve optimal energy management strategy of hybrid electric vehicle [19 - 21].

In this study, we investigated three approaches for instantaneous vehicle speed prediction in urban intersections. We propose a Prediction-based EAD as a velocity advisory system that makes full use of activity information of preceding vehicle. 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). Using SPaT information and future states of the preceding vehicle predicted by RBF-NN based forecasting model, the enhanced EAD algorithm provides an eco-friendly speed trajectory in the presence of preceding traffic and queues at intersections. The dataset from the Next Generation SIMulation (NGSIM) program [22] have been applied 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 the prediction-based EAD system architecture with elaboration on each components. Section IV presents a detailed description of the vehicle speed forecasting model and enhanced vehicle trajectory planning algorithm (EVTPA), followed by a comparative numerical simulation study and result analyses in Section V. The last section concludes the paper with further discussion.

II. BACKGROUND

A. *Existing Eco-Approach and Departure 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 deterministically defined with the available SPaT and GID information. The EAD application for fixed-time signals has shown 10%-15% reduction on fuel consumption and emissions in microscopic simulation models [10] and 13% - 14% saving from real world testing [15]. An enhanced EAD application has shown satisfactory results for congested urban traffic conditions in a fully connected environment [16]. Extended efforts have been made to develop an EAD application for actuated signals [17]. Most of the existing EAD studies focused on the interaction between the subject vehicle and the traffic signals [15]-[18]. Those applications work well under light traffic conditions, but are not effective in congested traffic, especially when there are preceding vehicles or queues. Fig. 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

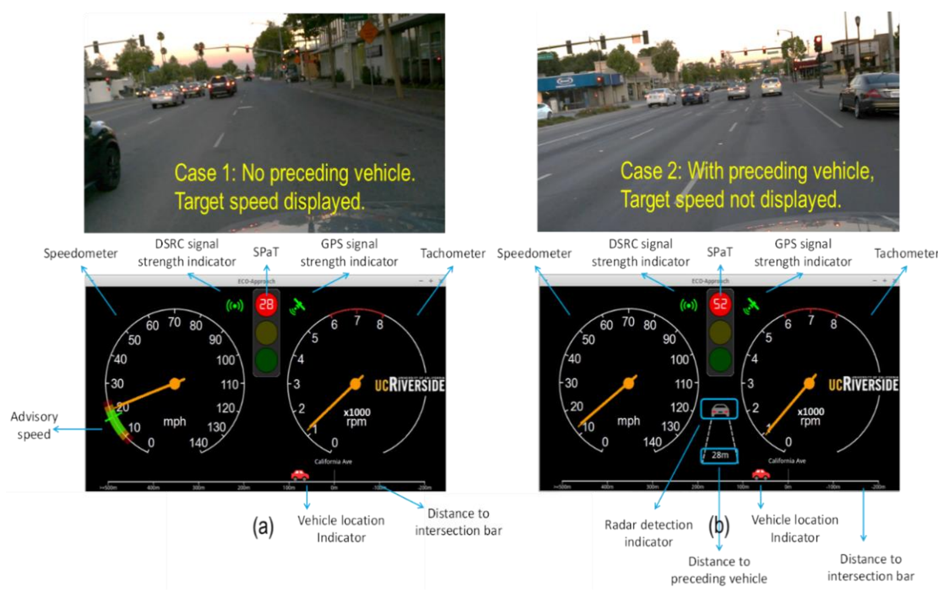


Fig. 1. Human-machine interface under different traffic condition.

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.

B. *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 various dynamic factors, e.g. signal status, surrounding vehicles' maneuver, and perhaps interruption from pedestrians. In the literature, various approaches for vehicle speed prediction have been investigated and evaluated [23-31]. 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) [23]. 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 [24]. On the other hand, data-driven approaches have recently been 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) [25]-[28]. In [26], 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 in the highways. Considering the requirement for large sampled vehicle trajectories and complexity of maneuver recognition in urban areas, it is challenging to apply it 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 [27]. Artificial Neural Networks (ANNs) have been proven to be an effective method for accurately forecasting vehicle speed and position, due to their strong capability of capturing the complex and nonlinear dynamics [28]-[30]. 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 [31]. Some approaches (i.e. TrackT [32] and TMicroscope [33]) have been proposed to enhance and precise tracking RFID systems to retrieve trajectory information. These approaches could provide real time trajectory information with high accuracy which can be further combined with advanced predictors to improve the overall performance.

III. System Architecture

In this work, our goal is 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 Fig. 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. In order to get preceding vehicle's second-by-second future states within the prediction horizon, a RBF neural network forecasting model is developed considering its benefits in terms of predictive accuracy, efficiency and applicability for real time implementation. The Enhanced Vehicle Trajectory Planning Algorithm (EVTPA) is able 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 EVTPA with the consideration of preceding traffic. As we highlighted in the flow chart, incorporation of real-time prediction of preceding vehicle's state into vehicle dynamic management (i.e. speed, acceleration) is the key contributions of this paper.

IV. Methodology

A. *Learning-based Vehicle Speed Forecasting Models*

A reliable and accurate prediction on preceding vehicle's state is essential for efficiently applying EAD strategy in congested urban traffic conditions. As aforementioned, a number of studies have evaluated various time series prediction approaches for predicting segment/link-level vehicles' speeds or under the highway scenarios. However, to the best of our knowledge, none of them have discussed the prediction performance for microscopic urban driving. The real time prediction of vehicle second-by-second speed trajectory along the signalized corridors is much more challenging due to the various disturbances from signals, traffic queues and pedestrians. Other than the vehicle speed prediction at a macroscopic level using traffic condition, historical traffic data as inputs which are usually not applicable for real time implementation, we aim at developing a direct time series forecasting model with vehicle second-by-second speed trajectory detected by onboard sensor (i.e. radar) as inputs. The historical speed horizon of the input and forecasting horizon of the output are both three time steps (i.e., 3 seconds) for training and testing the speed forecasting models.

In this study, we implement a Radial Basis Function Neural Network (RBF-NN) [34] for vehicle speed forecasting and compare its performance with other well-known nonlinear regression models like Gaussian Processes (GP) and Multi-Layer Perceptron Neural Network (MLP-NN) for different driving scenarios. The general RBF-NN based vehicle speed predictor has a feed-forward neural network framework with one hidden layer in which the nodes have radial transfer function as shown in Fig. 3. The network input is a vector containing the preceding vehicle's historical speed trajectory of last 3 seconds, and the output is predicted speed trajectory within a 3-second horizon.

The implemented RBF-NN is a three-layer feed-forward networks with K hidden nodes. A radial basis function needs to be pre-defined 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:

$$\varphi_j\,(x) = exp\left[-(\bar{x}-\mu_j)^T\,\textstyle\sum_j^{-1}(\bar{x}-\mu_j)\right] \tag{1}$$

$$y_k(x) = \textstyle\sum_{j=1}^{M} w_{kj}\,\varphi_j\,(x) + b_{kj} \tag{2}$$

where φ_j is the activated function of node j; $\bar{x}$ is the input vector for node j; w_{kj} is the output weights and b_{kj} is the constant bias; μ_j and $\sum_j$ are the mean vector and covariance matrix of the j^{th} Gaussian function. The mean μ_j represents the center and $\sum_j$ 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.

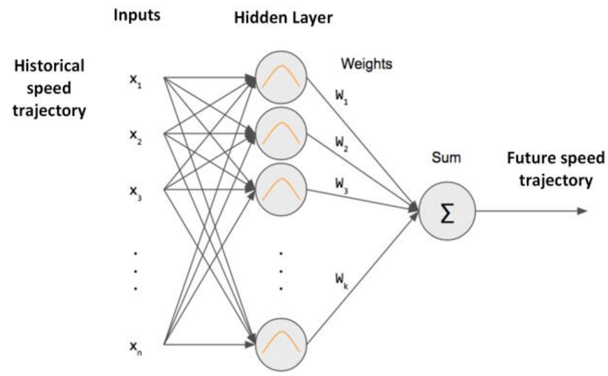


Fig. 3. RBF-based vehicle speed predictor structure

An advantage of RBF neural network compared to Gaussian Process and MLP neural network is that the efficiency on training based on two-stage procedure. The time complexity of training Gaussian Process for prediction are exponential growth with the sample size which is quite an issue when applied to large network in real time. MLP network could have more than one hidden layers and it uses iterative technique and work globally while RBF network has only one hidden layer and is based on non-iterative technique and acts as local approximation. Besides, RBF network shows more robustness to adversarial noise and easier generalization compared to MLP neural network. In the first stage of RBF-NN training, the parameters of the basis function are set to model unconditional data density. The centers of our trained RBF network are determined by fitting a Gaussian mixture model with circular covariance using the Expectation-Maximization (EM) algorithm. The second stage of training determines the weights between the hidden layer and the output layer by using Moore-Penrose generalized pseudo-inverse which overcomes many issues in traditional gradient

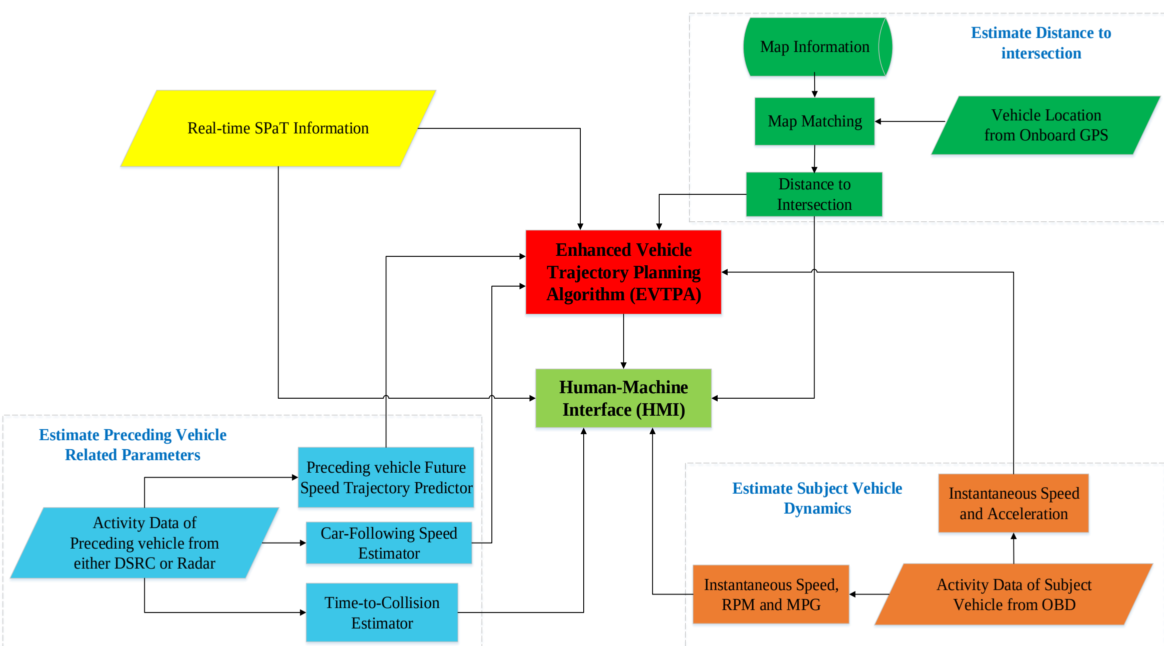


Fig. 2. Prediction-based EAD system architecture

algorithms such as stopping criterion, learning rate, number of epochs and local minima. The structure of RBF-NN is optimized by pruning the network based on 5-fold cross validation in this study. Due to its shorter training time, forecasting accuracy and generalization ability, RBF-NN is our selected approach for real-time vehicle speed forecasting in urban driving.

B. Enhanced Trajectory Planning Algorithm (EVTPA) with Consideration of Preceding Traffic

The EVTPA was 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 [35] as show in (3) to develop a trajectory that is safe and energy-efficient.

$$v_n(t+\tau) = \min\left\{ \begin{array}{l} v_n(t) + 2.5 a_n \tau \left(1 - \frac{v_n(t)}{v_n^d}\right)\sqrt{0.025 + \frac{v_n(t)}{v_n^d}}, \\ b_n\tau + \sqrt{b_n^2\tau^2 - b_n\left[2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t)\tau - v_{n-1}(t)^2 / b\right]} \end{array} \right\} \tag{3}$$

Where τ is the reaction time; $v_n(t)$ and $v_{n-1}(t)$ are the speed of the following vehicle n and the leading vehicle n-1 at time step t, respectively; v_n^d is the vehicle n desired speed; a_n is the vehicle n maximum acceleration; b_n and b are the most severe braking that the driver of vehicle n wishes to undertake and the expected leading vehicle maximum deceleration, respectively.

The proposed EVTPA is illustrated by the overall flow diagram in Fig. 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. V_P and V_S are preceding vehicle speed and subject equipped vehicle speed, respectively. Further, d is the distance of the subject vehicle to the stop bar at the signalized intersection.

To predict time delay and queue effect on the preceding vehicle, the first thing we need to estimate is whether the vehicle is going to join the queue or not. Fig.5 indicates the method we applied to determine whether or not the preceding vehicle will join the queue. The discharge process has been shown to be fairly stable compared to the arriving process. Vehicle's discharge pattern is observed to be close to uniformly distributed, leading to a relative constant discharge rate of the queue. Therefore, a queue dissipation rate w and vehicle spacing headway Δh_q were calibrated using the collected historical data. Based on the traffic counts k and the calibrated queue spacing, we could estimate the queue length $\hat{y}_b$ in Eq.4. The travel time for the preceding vehicle and the dissipation shockwave w to reach the location could be obtained by Eq. 5, 6, respectively.

$$\hat{y}_b = \mathrm{k} \times \Delta h_q \tag{4}$$

$$\bar{v}_{c:c+\Delta T} * (t_b - t_c) = d_1 - x_c - \hat{y}_b \tag{5}$$

$$\mathrm{w} * \left(t_w - T_g^n\right) = \hat{y}_b \tag{6}$$

where t_c represents the current time step, $\bar{v}_{c:c+\Delta T}$ is the current average forecasting speed of the preceding vehicle in

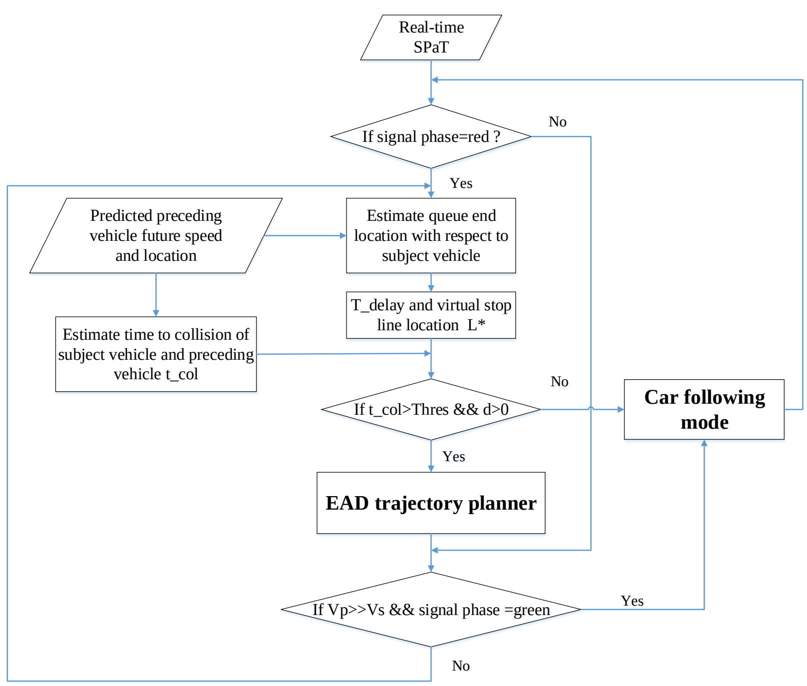


Fig. 4. Flow diagram of the enhanced vehicle trajectory planning algorithm (EVTPA)

short time horizon ΔT, t_b is the time step when preceding vehicle reach the queue end location, t_w is the time step when dissipation shockwave reaches the queue end location.

As it is shown in Fig.5, if $t_b < t_w$, which indicates the preceding vehicle reach the queue end before the dissipation shockwave, then the preceding vehicle will be part of the queue in the current cycle. Otherwise, the dissipation shockwave reaches the location before the preceding vehicle indicates the queue will be discharged already at the time when preceding vehicle approaching the intersection. Therefore, we could predict the distance to the virtual stop bar L^* *and* T_{delay} for Prediction-based EAD to avoid preceding queue effect as follows:

$$L^* = x_c + v_c \times \Delta T + \frac{(v_{c+\Delta T} - v_c)}{2}\Delta T + \frac{{v_{c+\Delta T}}^2}{2d} + L_{buffer} \quad (7)$$

$$T_{delay} = T_g + \frac{d_1 - L^*}{w} \quad (8)$$

where, v_c is the current speed and $v_{c+\Delta T}$ is the last forecasting speed within the time horizon; L_{buffer} is the distance buffer to the preceding queue end considering the physical length of a vehicle plus a safe margin in the car following model; d_1 is the current distance to the actual stop bar and .

The EAD trajectory planner takes the time delay (T_{delay}) caused by the preceding queue and distance to the estimated virtual stop line (L^*) 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 (t_{col}) based on the preceding vehicle's movement to guarantee safety in the planned maneuver. If the subject vehicle is under the risk of collision in the near future, car following mode will take over to guide the driver through the intersection while keeping safety distance from the

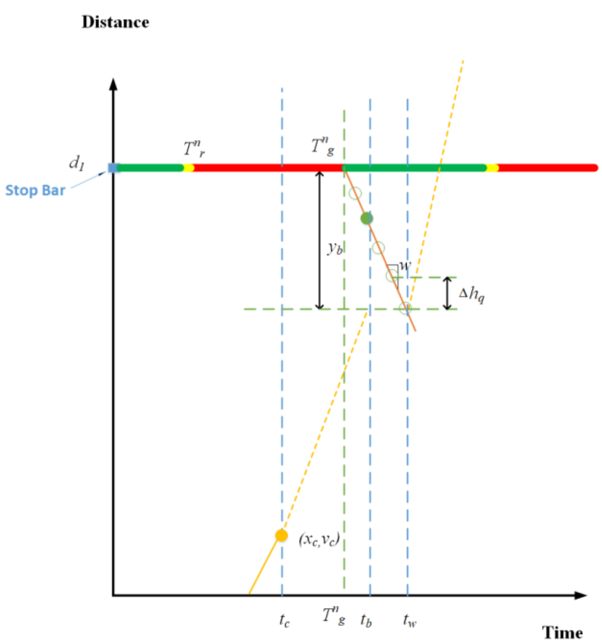


Fig. 5. Methodology for deciding whether preceding vehicle in the

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. With the computed virtual stop line and time delay at the signalized intersection, we choose the optimal acceleration and deceleration based on Eq. 9-12 that define a trigonometric function of the velocity with constraints of the vehicle tractive power, preceding vehicle's states, and riding comfort. The developed EVTPA based on piecewise sinusoidal acceleration/deceleration profiles was proposed to ensure that the subject vehicle ensures that the subject vehicle reaches the virtual stop line after the time delay caused by the preceding vehicle in order to avoid any impact from the downstream queue.

$$v = \begin{cases} \frac{v_m + v_c}{2} - \frac{v_m - v_c}{2}\cos(mt) & t \in \left[0, \frac{\pi}{m}\right) \\ v_m & t \in \left[\frac{\pi}{m}, \infty\right) \end{cases} \quad (9)$$

where v_c is the current speed and v_m is the speed limit from preceding traffic, m is the parameter that defines the acceleration and jerk profile. Eq. 9 generates the proposed sinusoidal speed profile. In this study, the maximum acceleration (a_{max}) is 2.5 m/s^2 and a maximum jerk (j_{max}) is 10 m/s^3. Then, m is selected as the maximum value that could meet the driving comfort and safety.

$$m = \min\left(\frac{2a_{max}}{v_m - v_c}, \sqrt{\frac{2j_{max}}{v_m - v_c}}\right) \quad (10)$$

The time length of the acceleration period is $\frac{\pi}{m}$, i.e., a half cycle. The distance d_a that the vehicle travels is:

$$d_a = \int_0^{\frac{\pi}{m}} \left[\frac{v_m + v_c}{2} - \frac{v_m - v_c}{2}\cos(mt)\right] dt = \frac{\pi}{m} \cdot \frac{v_m + v_c}{2} \quad (11)$$

Therefore, the minimum travel time of subject vehicle to reach the virtual stop line (queue end) at the intersection is:

$$t_{min} = \frac{\pi}{m} + \frac{L^* - d_a}{v_m} \quad (12)$$

where L^* is the distance away from the virtual stop line.

V. Results and Discussion

A. Data Descriptions

The NGSIM data collected from an arterial segment on Peachtree in Atlanta, Georgia are used for training and testing the vehicle speed forecasting models and evaluating the performance of the proposed Prediction-based EAD system. As shown in Fig. 6, there are 5 lanes and 4 intersections in the study corridor. The NGSIM Peachtree dataset includes the spatial and temporal information of all the vehicles as well as the traffic light information of four signalized intersections along the arterial segment from 12:45 p.m. to 1:00 p.m. and 4:00 p.m. to 4:15 p.m. on November 8, 2006 [22]. For data preparation, we randomly selected 70% of the real world data set for training and the rest 30% for testing. The SPaT information is also obtained for each signalized intersection based on the phase start/end time provided in the data. To develop accurate and reliable prediction of vehicle speed trajectory, we extract speed trajectory of each individual vehicle second by second 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. The total sample size for training the vehicle speed forecasting model is 9878; and for testing is 4234. In addition, the traffic signal status and distance to the stop-bar jointly impact the driver behavior when approaching a signalized intersection. Therefore, we classify the predicted speed trajectories into three groups based on different driving scenarios. In Scenario 1, the vehicle is approaching the intersection far from the stop-bar with the red signal phase; In Scenario 2, the vehicle is close to the stop-bar but current signal phase is still red; In Scenario 3, vehicle approaching the intersection with green signal phase. The classified vehicle speed trajectories are used for developing and evaluating the vehicle speed forecasting models in each scenario, respectively.

B. RBF-based Vehicle Speed Forecasting Model

The RBF network comprises a typical three layers: input, hidden and output. Each neuron of the hidden layer represents a kernel or basis function. Here, we apply Gaussian function as the basis function to account for the non-linearity and the Gaussian function responds only to a small region of the input space where the Gaussian is centered. The key to a successful forecast vehicle speed trajectory based on RBF network is to find suitable centers for each Gaussian function, which is characterized by two parameters: center (μ_j) and peak width ($\sum_j$) as shown in Eq. 1. The output from the jth Gaussian neuron for an input speed measurement x_i can be obtained by Eq.2. The RBF hidden layer is fully connected to the output layer by the size of the weight coefficient, w_{kj} and the constant bias b_{kj}. The weights w_{kj} are adjusted to minimize the mean square error of the forecasting outputs. There are two sets of parameters (the centers and the widths) in the hidden layer and a set of weights in output layer are adjusted, and the RBF neural network has a guaranteed learning procedure for convergence. The calibrated RBF network consists 15, 10, 15 neurons in hidden layer for each aforementioned driving scenario, respectively. For scenario I and III, calibrated center is a 15 by 3 matrix, peak width is a vector with length 15, weights of hidden layer is a 15 by 3 matrix and bias is a 3 by 1 vector. For scenario II, calibrated center and weights' dimension are both 10 by 3, peak width is 10 by 1 and bias is 3 by 1. The details of calibrated parameters of the developed RBF-network can be accessed in the supplement material of this paper.

To generate the short-term forecasting vehicle trajectory, one of the developed RBF networks is called based on the current driving scenario at each time step to provide a 3-sec vehicle future speed trajectory as illustrated in Fig.6. The solid black line is an example vehicle trajectory and the colored short lines represent our RBF-based short-term speed forecasting results over time. Fig.6 shows the developed RBF-based vehicle speed forecasting model can provide reliable prediction based on the historical speed profile.

C. Evaluating the Performance of Vehicle Speed Forecasting Models

The evaluation and comparison of the vehicle speed forecasting models based on three different nonlinear regression methods (RBF network, MLP network, Gaussian Process) are conducted using real world driving data collected in urban traffic (NGSIM Peachtree data). The program was written in MATLAB and evaluated on a computer with i7 CPU @ 2.80GHz and 16 GB memory.

The parameters for nonlinear regression models were selected by K-fold (K=5) cross validation. For the MLP network, we selected the log-sigmoid function as the nonlinear activation function and trained by a back-propagation algorithm. The optimal network structure of MLP network includes two hidden layers with 20 neurons in the first hidden layers and 10 neurons in the second.

The Root Mean Square Error (RMSE) is also adopted in this study to measure the time series forecasting accuracy, defined as:

$$RMSE = \sqrt{\sum_{N} (y-\hat{y})^2 / N} \tag{4}$$

where N is the number of measurements, y and $\hat{y}$ indicate the actual value and predicted value, respectively.

A summary of the comparative results of vehicle speed forecasting models based on RBF-NN, MLP-NN and GP can be seen in Table I in terms of their forecasting accuracy and computational cost for both training and testing. RMSEs of the predicted vehicle speed trajectories based on RBF-NN with respect to the ground truth under three driving scenarios are 4.3 ft/s, 1.7 ft/s and 4.9 ft/s, respectively. For all three driving scenarios, RBF-NN speed forecasting model outperforms the other two approaches: MLP-NN and GP in terms of prediction accuracy. Although in scenario III, RMSE shows that GP and RBF-NN perform similarly well, it is quite time consuming on training a GP based forecasting model for large dataset. It is noted that the time cost for training GP is significantly higher than training MLP-NN or RBF-NN in Scenario II and III, because it is cubically increased with respect to the size of the measurements. The forecasting speed represents for a given vehicle trajectory, how long it takes the trained vehicle speed forecasting model to return the predicted results. As shown in Table I, the forecasting time for RBF-NN is about 10^{-3}~10^{-4} s; for MLP-NN is about 10^{-1}~10^{-2} s and for GP is about 0.1 s. RBF network has the highest forecasting speed among the three forecasting models which makes it much more promising for real time applications. Therefore, we selected RBF-NN as our forecasting model to predict the preceding vehicle's speed trajectory which is applied to Prediction-based EAD system.

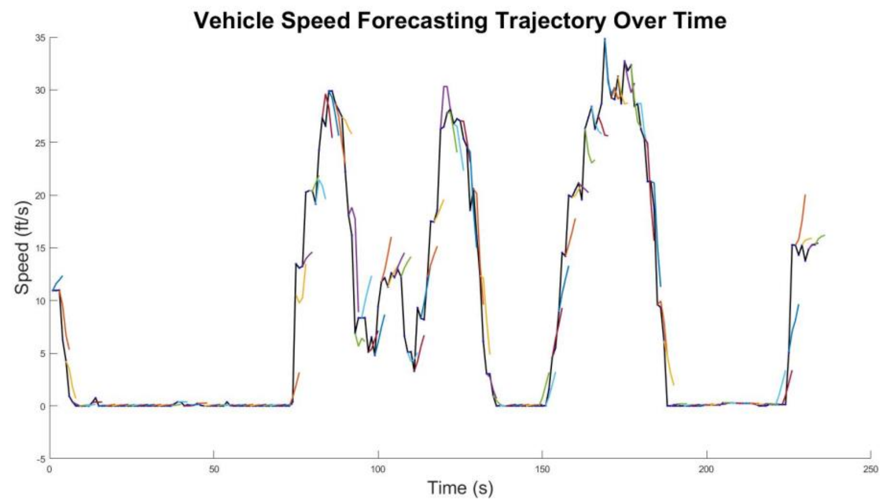
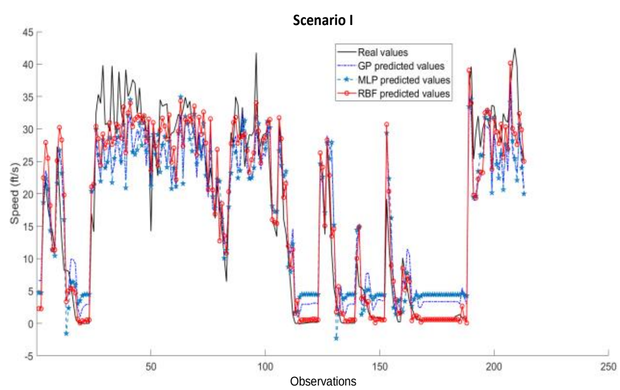
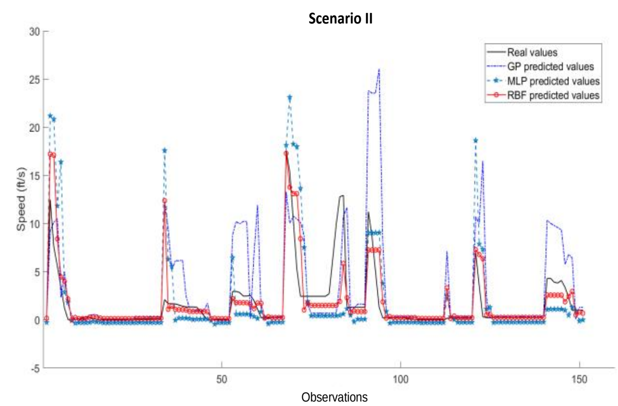


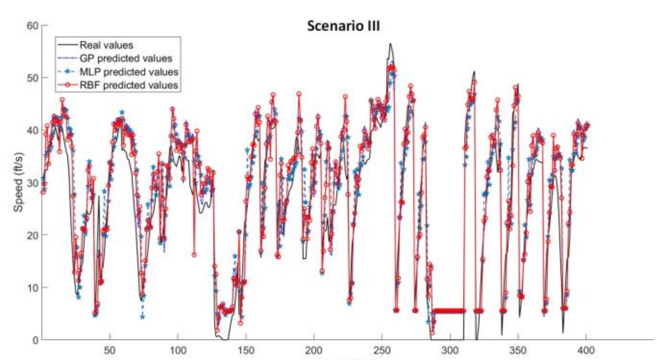
Fig. 6. Vehicle speed forecasting results with 3 second prediction horizon using RBF-NN



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



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



(c) Scenario 3: Green signal phase

Fig. 7. Results of vehicle speed forecasting under different driving scenarios

TABLE I. COMPARATIVE RESULTS OF VEHICLE SPEED FORECASTING MODELS BASED ON DIFFERENT METHODS

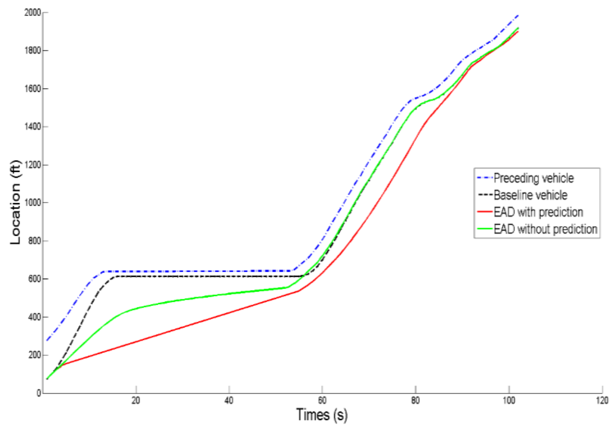
Performance		**RBF-NN**	**MLP-NN**	**GP**
RMSE (ft/s)	**Scenario I:**	4.3	5.8	5.6
	Scenario II:	1.7	3.7	3.2
	Scenario III:	4.9	6.1	5.5
Training Time (s)	**Scenario I:**	0.03	1.6	0.9
	Scenario II:	0.5	2.1	63.5
	Scenario III:	0.3	1.7	22.6
Forecasting Time cost (s)	**Scenario I:**	10^{-4}	0.1	0.1
	Scenario II:	10^{-3}	0.03	0.2
	Scenario III:	10^{-3}	0.02	0.2

Fig. 7 illustrates the predicted average speed within the prediction horizon of 3 seconds based on three different forecasting model vs. the ground truth under three driving scenarios, respectively. As shown in Fig. 7, RBF-NN is able to provide reliable results with satisfactory prediction accuracy for each driving scenarios. Although all three forecasting models: RBF-NN, MLP-NN and GP show similar performance for Scenario III, RBF-NN has much better prediction results for Scenario I and II, compared to MLP-NN and GP.

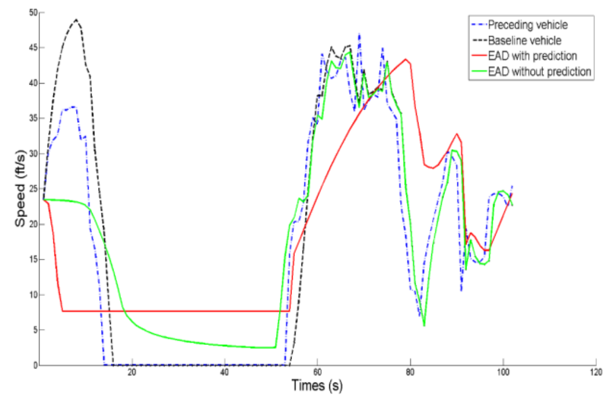
D. Validation of the Trajectory Planning Algorithm with Traffic

In this study, we only consider the straight movement through the intersection. In this case, we take all the northbound through movement vehicles in the NGSIM Peachtree dataset as preceding vehicles (185 vehicles in total) after filtering out the trajectories on the side streets. Then, three different types of subject vehicles (baseline vehicle, EAD without prediction vehicle, EAD with prediction vehicle) are simulated as driving behind that preceding vehicle through signalized intersections for further comparison. More specifically, the baseline vehicle is the subject vehicle that is simulated based on the car following strategy (i.e., Gipps's car following model in this study). For the EAD without prediction case, the vehicle switches from EAD to car following state if the relative distance to the preceding vehicle is less than a threshold (i.e., 70 ft) to guarantee safety. The EAD with prediction vehicle is the subject vehicle equipped with the proposed prediction-based EAD system. It is noted that the preceding vehicle trajectories were generated from real world driving data in NGSIM and were used as the inputs to the proposed prediction method.

Fig. 8 compares the estimated trajectories and speed profiles from different models in response to the trajectory of an example preceding vehicle. It illustrates how the proposed



(a) Time-space trajectories

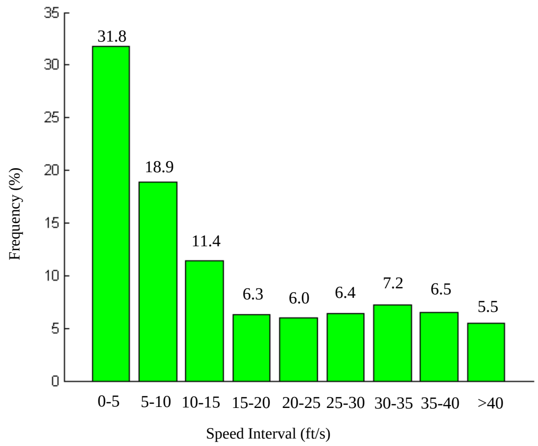


(b) Speed profiles

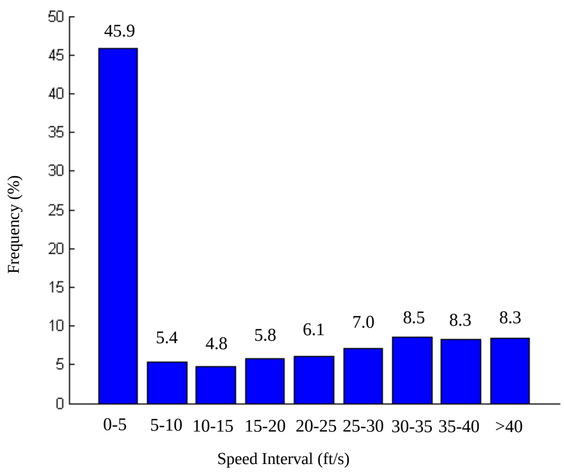
Fig. 8. A comparison of different driving strategy

prediction-based EAD system reduces unnecessary idle time and speed oscillation, while keeping a safe distance from the preceding vehicle when driving through signalized corridors. As shown in Fig. 8, the EAD system without prediction can reduce unnecessary acceleration and deceleration compared to the baseline when the subject vehicle is far from the preceding. However, without prediction of the preceding vehicle's activity, the subject vehicle may lead to a sudden deceleration to a very low speed (<5 ft/s) or even a full stop due to constraints from the preceding vehicle. In contrast, the prediction-based EAD system can enable the subject vehicle to drive through the signalized intersection in a much smoother maneuver based on the prediction of the preceding vehicle's activity and the queue end. This can significantly reduce the fuel consumption and emissions by avoiding unnecessary idling and further smoothing the speed profile.

In Fig. 9, we summarize the speed distributions of EAD with prediction vehicles and EAD without prediction vehicles over the total 185 test vehicle trajectories. There is a significant drop on the percentage of idling or low-speed (<5 ft/s) scenarios for vehicles with the prediction-based EAD system in Fig. 9(a) compared to EAD without prediction vehicles in Fig. 9(b). Meanwhile, the percentage of vehicles driving at high speed (i.e. speed larger than 40 ft/s) is significantly reduced. Those findings imply the proposed prediction-based EAD system is able to further reduce unnecessary idling, accelerations and decelerations even in the congested urban traffic.



(a) Speed distribution for EAD with prediction vehicles



(b) Speed distribution for EAD without prediciton vehicles

Fig. 9. Impact of proposed Prediciton-based EAD system on vehicle speed distribution

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 [36] is applied. The MOVES model is the state of art emission simulator developed by the U.S. Environmental Protection Agency (USEPA). The model is designed to estimate energy consumption and emissions for mobile sources on a macroscale, mesoscale or microscale. The second-by-second Vehicle Specific Power (VSP) can firstly be calculated based on the 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 function of VSP, speed and acceleration values. Finally, with the OpMode distribution, the energy consumption and emissions of all the vehicle trajectories are estimated based on the emission factors from MOVES database.

TABLE II. 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)**	**$PM_{2.5}$ (mg/ mile)**
Baseline vehicle	0.44	8.08	1.14	689	9586	26.7
EAD without prediction	0.43	7.67	1.06	674	9384	23.3
EAD with prediction	0.41	6.85	0.81	662	9207	15.5
Saving in % (baseline)	5.2	15.3	28.3	4.0	4.0	41.7
Saving in % (EAD without prediction)	3.1	10.8	23.3	1.9	1.9	33.4

Based on the MOVES model, Table II shows the energy and environmental benefits of the total 185 vehicle trajectories generated by the proposed prediction-based EAD system, compared to the baseline and EAD without prediction, respectively. Results show that the subject vehicles equipped with proposed prediction-based EAD system has average 4.0% and 1.9% improvement in terms of energy savings with respect to baseline and EAD without prediction, respectively. In addition, significant reduction in air pollutant emissions of the prediction-based EAD-equipped vehicle can be observed from Table II. The emissions of HC, CO, NOx, CO2 and PM2.5 per mile in the prediction-based EAD equipped vehicles are 5.2%, 15.3%, 28.3%, 4.0%, 4.0% and 41.7% less than the baseline vehicles, respectively. It turns out that the proposed prediction-based EAD system also reduce of 3.1% HC, 10.8% of CO, 23.3% of NOx, 1.9% of CO2 and 33.4% of PM2.5 per mile compared to EAD without prediction. The prediction-based method also shows its advantage in safety performance. For the EAD without prediction system, the drivers may need to frequently switch from EAD mode to their own decision. This may lead to long perception/reception time and cause potential sharp braking or even accident. The prediction module would provide a smoother trajectory in the EAD-car following transition and enhance the safety.

VI. CONCLUSIONS

This research proposes a prediction-based EAD system for real-time implementation that enables the driver to travel through a signalized intersection in a safe and eco-friendly manner in urban traffic. The comparative validation results indicate that the proposed RBF-NN model outperforms MLP-NN and GP models in terms of accuracy and computation time for predicting preceding vehicle's speed trajectory under different scenarios. Based on SPaT and GID information as well as predicted states of preceding vehicle, the proposed EAD algorithm can provide a smooth 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 4.0% of energy and reduce air pollutant emissions by 4.0%~41.7% compared to conventional vehicles (simulated by Gipps' car-following model). It turns out that the prediction-based EAD system saves 1.9% energy and reduces 1.9% to 33.4% air pollutant emissions compared to EAD without prediction in congested traffic condition.

VII. Acknowledgements

This study is partially supported by the National Center for Sustainable Transportation (NCST). The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views from NCST.

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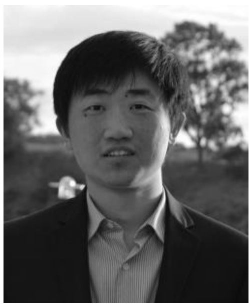

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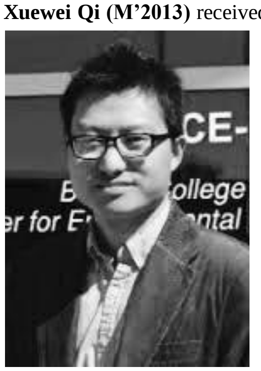

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