Velocity Optimization of Pure Electric Vehicles with Traffic Dynamics Consideration

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***Abstract*—As Electric Vehicles (EVs) become increasingly popular, their battery-related problems (e.g., short driving range and heavy battery weight) must be resolved as soon as possible. Velocity optimization of EVs to minimize energy consumption in driving is an effective alternative to handle these problems. However, previous velocity optimization methods assume that vehicles will pass through traffic lights immediately at green traffic signals. Actually, a vehicle may still experience a delay to pass a green traffic light due to a vehicle waiting queue in front of the traffic light. In this paper, for the first time, we propose a velocity optimization system which enables EVs to immediately pass green traffic lights without delay. We collected real driving data on a 4.0 *km* long road section of US-25 highway to conduct extensive trace-driven simulation studies. The experimental results from Matlab and Simulation for Urban MObility (SUMO) traffic simulator show that our velocity optimization system reduces energy consumption by up to 17.5% compared with real driving patterns without increasing trip time.**

I. Introduction

In contrast to traditional vehicles, Electric Vehicles (EVs) cause less environmental pollution since the sources of electricity can be renewable energy sources. As a result, EVs have drawn great attention and are predicted to dominate the global market in the near future. However, EVs have battery-related issues such as shortage driving range, high production cost and heavy weight of large batteries. Besides, frequent charging/discharging reduces battery lifetime. Thus, increasing EV energy efficiency is very important to mitigate these battery-related issues and increase the usage of EVs, especially for pure EVs which have battery cells as sole power source. Among various strategies to increase energy efficiency, velocity optimization is one of the most effective methods.

Since more sudden stops and accelerations generate higher energy consumption, the objective of velocity optimization is to reduce the number of sudden stops and accelerations [1]–[5]. One group of previous works [1], [3] relies on roadside units to calculate the vehicle's optimal velocity profile from its source to destination. In another group [4], [5], each vehicle communicates with traffic signals so that vehicles can pass traffic signals without any brakes to reduce the total numbers of sudden stops and accelerations. Considering computation complexity of velocity profile optimization, a computing framework for transportation systems, called vehicular cloud, has been proposed [6], [7]. In this framework, each vehicle uploads it state (starting time and route) to the cloud through wireless communication [8], and then the cloud calculates the optimal velocity profile for the vehicle.

Though many efforts have been devoted to optimizing vehicle velocity to reduce energy consumption, existing works assume that vehicles will pass through traffic lights immediately at green traffic signals without any delay [2], [4], [5]. However, there may be some vehicles waiting in front of a traffic light when the signal turns green. It usually takes some time for these vehicles to accelerate and pass through the traffic light. To the best of our knowledge, velocity optimization with the consideration of delay passing green traffic lights has not been explored so far in the literature. In this paper, we propose a dynamic programming (DP)-based velocity optimization system for EVs which considers waiting vehicle queue dynamics in traffic light areas. Since waiting vehicle queue is greatly affected by the traffic volume, which is highly unpredictable and dependent on different times (e.g., time of a day, day of a week, week of a month, month of a year, etc.) and different incidents (e.g., traffic accidents, public concerts, festivals, etc.), the main challenge here is *how to accurately predict the number of vehicles waiting in front of a traffic light so that EVs can pass through the traffic light without delay*.

To handle this challenge, we build a queue length (QL) model and estimate the number of vehicles waiting in a traffic light area based on vehicle arrival rate and leaving rate ($vehicles/hour$) [9]. Unlike the previous QL models [9] that assume the vehicle arrival rate and leaving rate are pre-known, our QL model more accurately predicts the two rates. To predict vehicle arrival rate, we use the deep learning-based Stacked autoencoders (SAE) model [10], which can accurately predict traffic volume. To predict vehicle leaving rate, we design a vehicle movement (VM) model to describe velocity dynamics during acceleration process when the traffic light turns green. Then, based on the queue length (i.e., the number of vehicles in front of the traffic light), our DP algorithm finds a velocity profile that enable an EV to pass traffic lights immediately without meeting waiting queues.

To verify our DP-based velocity optimization system, we chose a 4.0 *km* long road section of US-25 highway for our experimental study and collected velocity traces by driving on this road section. The experimental results from Matlab and Simulation for Urban MObility (SUMO) traffic simulator show that our system helps vehicle pass through traffic lights without any delay or stops and reduce energy consumption comparing with other real and optimal velocity profiles. Also, our velocity optimization system greatly reduces energy consumption compared with existing velocity optimization methods.

Our contributions are summarized below:

- We propose DP-based velocity optimization model which considers queue dynamics in traffic light areas and aims to avoid the acceleration/deceleration in traffic light areas to minimize energy consumption. More specifically, queue length in front of a traffic light is predicted using our established QL model, which uses deep learning-based SAE model and our established VM model to predict vehicle arrival rate and leaving rate, respectively.
- We conduct extensive simulation studies to verify proposed systems based on Matlab and SUMO traffic simulator. The experimental results show that proposed velocity optimization method helps EVs reduce total energy consumption by 8.4% and 17.5% compared with velocity profiles in mild driving and fast driving.

The rest of this paper is organized as follows. In Section II, we present how to predict the queue length in traffic light areas and integrate QL model into the DP-based algorithm to optimize velocity profiles. We present experimental evaluation in Section III. Section IV introduces related research work. Finally, we conclude this paper in Section V with remarks on our future work.

II. System Design

In this section, we firstly build an energy consumption model for EVs which is then used in the optimization process. Then, we present our velocity optimization system.

A. Energy Consumption Model of Electric Vehicle

There are several existing models [11] for fuel consumption of vehicles. These models are not sufficiently accurate mainly because they are built based on empirical studies and do not consider the effect of road grade on energy consumption. To overcome this problem, we propose a new energy consumption model. It can figure out corresponding driving force changes when a vehicle passes through a road with different road grades in order to more accurately estimate energy consumption.

When an EV drives on the road with road gradient θ, The required force, F_{drive}, to drive the EV with velocity v is as follows [2], [12]:

$$F_{drive} = m\frac{dv}{dt} + \frac{1}{2}\rho A_f C_d v^2 + mgsin\theta + \mu mgcos\theta \quad (1)$$

where m is gross weight, ρ is average air density, A_f is frontal area of the vehicle, C_d is drag coefficient, θ is road gradient, μ is rolling resistance coefficient and g is gravity constant. Then, the energy E for driving EV can be described by Equ. (2) [13] :

$$E = UQ\eta_1\eta_2 \quad (2)$$

where U is the voltage of battery pack and Q is total charge consumption, η_1 and η_2 represent battery energy transforming efficiency and powertrain working efficiency, respectively. For EVs, the energy consumption can be indicated with electrical charge consumption (Ampere hour) for convenience in the practice. Then, the energy consumption rate, ζ, is calculated as follows:

$$\zeta = \frac{F_{drive}v}{U\eta_1\eta_2} \quad (3)$$

B. Traffic Dynamics in Traffic Signal Areas

Avoiding any type of accelerations or decelerations helps to reduce energy consumption. If queue length (i.e., the number of vehicles waiting in a traffic light area) can be predicted in advance, optimal velocity profile of an EV can be created to enable it to immediately pass the area without any accelerations, decelerations or stops. In this paper, we predict the number of vehicles in a traffic light area by building a QL model [9]. In the following, we first present the deep learning-based SAE model for vehicle arrival rate prediction. Then, we propose a VM model to predict vehicle leaving rate. Finally, we build a QL model based on the vehicle arrival and leaving rates to more accurately estimate the vehicle queue length.

1) Arrival vehicle rate: We estimate vehicle arrival rate at a traffic light area using the existing deep learning-based SAE model, which can accurately predict traffic volume. The traffic volume prediction is a temporal and spatial process and can be described as follows: $X(t)$ is used to represent traffic volume of an observation station (i.e., location) at time t. Given a sequence of traffic volume $X(t)$ values, the aim of the traffic flow model is to accurately predict the traffic volume $X(t + \Delta)$ after a time interval Δ. Compared with other methods in traffic volume prediction, the deep learning-based SAE model provides hierarchical feature extraction and has higher prediction accuracy [10]. Therefore, we choose the deep learning-based SAE model to predict traffic volume. When SAE model is applied to predict traffic volume at time $t + \Delta$, historical traffic volume $V_{in}(t)$ and the specific time t are chosen as inputs. The output of the model is estimated traffic volume, $V_{in}(t+\Delta)$, which is the vehicle arrival rate in a traffic light area.

2) Vehicle leaving rate: Current methods [2], [4], [5] assume that the vehicles waiting in a traffic light area will pass the traffic light immediately when the green traffic light is on. However, this assumption does not consider the vehicle acceleration process when the traffic light turns green due to the vehicle waiting queue in front of traffic light (Fig. 1). Here we build a VM model to consider vehicle acceleration process.

In the VM model, we assume that the waiting vehicles in a traffic signal area accelerate from 0 to minimum speed limit v_{min} with maximum acceleration value a_{max} from the beginning of green traffic period. Then, the vehicles maintain constant velocity v_{min} when passing through the traffic light area. Note that a driver's response delay to the traffic lights is not be considered here as it is beyond our current focus. We consider a traffic light cycle consisting of a time period for red light (from 0 to t_{red}) and a time period for green light (from t_{red} to t_{green}). We use t to denote the current time, use v_{opt} to denote the optimal velocity in an EV's optimal velocity profile. We use t' to denote the time when all vehicles in the queue pass through the traffic light: $t' = \frac{1}{v_{min}-dV_{in}}(v_{min}t_1 - \frac{v_{min}^2}{2a_{max}})$.

So, the queue length at t' becomes zero. Based on the VM model, vehicle velocity $v(t)$ at one traffic light cycle can be described as in Equ. (4). We use v_{min} to denote the allowed minimum speed limit of the area of the traffic light.

$$v(t) = \begin{cases} 0, & 0 < t \leq t_{red} \quad (i) \\ a_{max}(t - t_{red}), & t_{red} < t \leq \frac{v_{min}}{a_{max}} + t_{red} \quad (ii) \\ v_{min}, & \frac{v_{min}}{a_{max}} + t_{red} < t \leq t' \quad (iii) \\ v_{opt}, & t' < t \leq t_{red} + t_{green} \quad (iv) \end{cases} \tag{4}$$

where $\frac{v_{min}}{a_{max}} + t_{red}$ is the time when the vehicle accelerates to v_{min}, Condition (i) means it is in the red light time period, so the EV's velocity is 0. Condition (ii) means when the light is green and the EV is accelerating. Condition (iii) means when the light is green and there are still vehicles in the front of the EV. Condition (iv) means when the light is green and there are no vehicles in the front of the EV.

Then, we can calculate vehicle leaving rate for a traffic light cycle. We assume that the average inter-vehicle distance $\bar{d}$ inside the queue is constant [14]. Since some vehicles in the queue do not always go straight and would choose to turn left or right, we define γ as the ratio between the number of vehicles going straight and the total number of vehicles. Vehicle leaving rate $V_{out}(t)$ can be calculated as shown in Equ. (5):

$$V_{out}(t) = \frac{v(t)}{\bar{d}\gamma} \tag{5}$$

Based on arrival and vehicle leaving rates, we develop a new QL model to predict the queue length in front of traffic light in the next section.

3) Queue length model: In QL model, when traffic light turns red, the vehicle firstly arriving at the traffic light will stop immediately and rear vehicles will decelerate and join in the queue. When traffic light is green, vehicles in the queue will accelerate to pass through the traffic light without delay. The dynamics of queue length model is shown in Fig. 1.

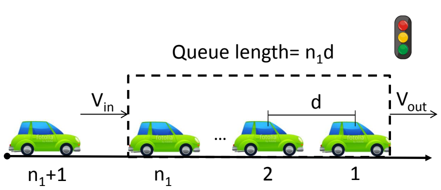


Fig. 1. A vehicle queue in front of a traffic light.

In our QL model, the queue length L_q during one traffic light period is calculated based on vehicle arrival rate V_{in}, vehicle leaving rate V_{out}, red traffic light time period t_{red} and green traffic light time period t_{green} in Equ. (4) and (5). We can describe QL model to analyze queue length dynamics in one traffic light time period as follows:

$$L_q(t) = \begin{cases} \bar{d}V_{in}t, & 0 < t \leq t_{red} \ (i) \\ \bar{d}V_{in}t - \frac{1}{2}a_{max}(t - t_{red})^2, & t_{red} < t \leq t_1 (ii) \\ \bar{d}V_{in}t - \frac{v_{min}^2}{2a_{max}} - v_{min}(t - t_1), & t_1 < t \leq t' \ (iii) \\ 0, & t' < t \leq t_2 \ (iv) \end{cases} \tag{6}$$

where $t_1 = \frac{v_{min}}{a_{max}} + t_{red}$, is the time when the vehicle accelerates to v_{min}; and $t_2 = t_{red} + t_{green}$ represents one traffic light time period. Based on above analysis, we can predict the time when queue length becomes zero and apply it in velocity optimization method.

In the next section, we discuss how to apply our QL model into DP-based velocity optimization method.

C. DP-based Velocity Optimization

As previous DP-based velocity optimization methods [2], we also use the DP algorithm to optimize velocity profile for an EV's route from its source to its destination. In the DP algorithm, all sets of feasible discrete velocities for a given route segment are formed at first. Then, energy consumptions for all discrete velocity sets are calculated and compared. Finally, the discrete velocity set with the minimum energy consumption is selected as the optimal velocity set. To improve the efficiency of the computation, we can use the method introduced in [15], which is orthogonal to the work in this paper.

In a current DP-based method, the road with B stop signs is divided into equal-distance point s_i, where $i = 0, 1, ..., f$. s_0 and s_d represent starting and destination points, respectively. A stop sign or a traffic light is located in a point. Several constraints such as speed limit, acceleration range and stop sign need to be considered to form discrete velocity sets. These constraints can be described as Equ. (7).

$$v(s_i) = \{v(s_i) : v_{min}(s_i) \leqslant v(s_i) \leqslant v_{max}(s_i)\} \tag{7a}$$

$$v(s_i) = \{v(s_i) : a_{min}(s_i) \leqslant \frac{dv(s_i)}{d(t)} \leqslant a_{max}(s_i)\} \tag{7b}$$

$$v(s_i) = \{0 : \sum_{k=0}^{i-1} d_{k,k+1} = P_b \text{ for } b = 1, 2, ..., B\} \tag{7c}$$

$$v(s_i) = \{0 : \text{for } i = 0 \text{ and } f\} \tag{7d}$$

where $d_{k,k+1}$ is the distance between point s_k and point s_{k+1}; $v_{min}(s_i)$ and $v_{max}(s_i)$ are minimum and maximum speed limits at point s_i; $a_{min}(s_i)$ and $a_{max}(s_i)$ are minimum and maximum acceleration values at the point s_i; P_b is the distance of the bth stop sign from the starting point.

Equ. (7a) means the velocity at location s_i must be within the required minimum and maximum velocities at s_i. Equ. (7b) means that the acceleration at location s_i must be within the allowed minimum and maximum acceleration values at the point s_i; Equ. (7c) and (7d) mean that the velocity at the stop sign, the source and the destination must be 0.

We use $a(s_i)$ to denote acceleration value between point s_i and s_{i+1} and then $v(s_{i+1}) = \sqrt{v(s_i)^2 + 2a(s_i)d_{k,k+1}}$. The optimal velocity set, $v'(s_i) = \{v'(s_0), v'(s_1), v'(s_2), ..., v'(s_d)\}$, is achieved by minimizing unit energy consumption from s_i to the destination s_d, $E(s_i)$, in Equ. (8):

$$E(s_i) = \underset{v(s_i)}{\text{argmin}}\{g_1(v(s_i), a(s_i)) + J_{(s_{i+1})}(v(s_{i+1}))\} \tag{8}$$

where $J_{(s_{i+1})}(v(s_{i+1}))$ is defined as the transition cost (i.e., energy consumption) function from point s_{i+1} to point s_d for the vehicle with initial speed $v(s_{i+1})$ and acceleration

$a(s_{i+1})$. The details of the cost function are introduced in [2]. $g_1(v(s_i), a(s_i))$ denotes the transition cost function from point s_i to point s_{i+1}, and it can be calculated by Equ. (9):

$$g_1 = \begin{cases} \zeta(v(s_i), a(s_i)), & (v(s_i), a(s_i)) \in C(s_i) \quad (i) \\ +\infty, & \text{otherwise} \quad\quad\quad\quad (ii) \end{cases} \tag{9}$$

where $\zeta(v(s_i), a(s_i))$ is energy consumption from point s_i to point s_{i+1} for EV with speed $v(s_i)$ and acceleration $a(s_i)$. It can be calculated based on Equ. (3). $C(s_i)$ are speed and acceleration limits in point s_i. $+\infty$ for Condition (ii) is set so that the velocity and acceleration outside of the $C(s_i)$ limit will not be chosen in DP-based optimal solution computation.

Our velocity optimization method is novel in that it considers queue lengths in front of traffic lights when optimizing velocity profiles so that an EV can immediately pass through traffic lights with no waiting vehicles (i.e., no accelerations or decelerations). Assume $t = 0$ when an EV is at the source location s_0. We also assume a traffic light is located at point s_i. For the EV driving with $v(s_i)$ in point s_i and driving with $v(s_{i+1})$ in point s_{i+1}, the average velocity from s_i to s_{i+1} equals $(v(s_i) + v(s_{i+1}))/2$. Then, the time $t(s_i)$ that an EV arrives at s_i from s_0 can be calculated using Equ. (10).

$$t(s_i) = \sum_{k=0}^{i} \frac{2d_{k,k+1}}{v(s_k) + v(s_{k+1})} \tag{10}$$

To ensure that an EV can pass through traffic light areas during green traffic signals with no waiting vehicles, we introduce a penalty function $f_2(v(s_i))$ described as Equ. (11).

$$f_2(v(s_i)) = \begin{cases} 1, & t(s_i) \in T_q \\ M, & t(s_i) \notin T_q \end{cases} \tag{11}$$

where T_q is the time period when queue length is zero, and M is a large constant. T_q can be calculated based on Equ. (6) by setting $L_q(t) = 0$. Using penalty function $f_2(v(t))$, new transition cost function $g_1(v(s_i), a(s_i))$ is re-defined as shown in Equ. (12):

$$g_1(v(s_i), a(s_i)) = \begin{cases} \zeta(v(s_i), a(s_i)), & \mathbb{A} \\ M\zeta(v(s_i), a(s_i)), & \mathbb{H} \\ +\infty, & \text{otherwise} \end{cases} \tag{12}$$

$\mathbb{A} = \{\ (v(s_i), a(s_i)) \in C(s_i)$ and $t(s_i) \in T_q\}$, which means that the discrete velocity set not only satisfies speed and acceleration constraints but also satisfies time period T_q. $\mathbb{H} = \{\ (v(s_i), a(s_i)) \in C(s_i)$ and $t(s_i) \notin T_q\}$, which means that discrete velocity set satisfies only speed and acceleration constraints but does not satisfy the time period T_q. Based on the new transition cost function, our proposed method can consider both multiple traffic lights and traffic dynamics in front of traffic lights simultaneously in velocity profile optimization. As a result, the DP-based optimal solution gives the optimal velocity profile for an EV to minimize its energy consumption.

III. Performance Evaluation

A. Experimental Settings

At first, we implemented energy consumption model, queue length model and DP algorithm using Matlab to do the experiments. We then conducted velocity experiments in SUMO traffic simulator. We found that both results are consistent to each other, so we only report the results from SUMO. For the experimental studies, we chose a road section on the US-25 highway located at Greenville, SC (Fig. 2). In this road segment, there are one stop sign at 490 m from the beginning and two traffic lights located at 2180 m and 3460 m from the beginning, separately. The parameter settings used in our experiments are given below.

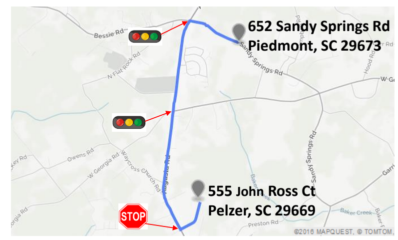


Fig. 2. Experimental road segment (US-25 at Greenville, SC).

1) Energy consumption model: Based on Chevrolet Spark EV (which has become widely popular), we built the vehicle model to calculate its energy consumption for different pairs of velocity sets. Considering riding comfort and safety, we considered a fixed range of acceleration (from -1.5 m/s^2 to +2.5 m/s^2) [2]. To satisfy power and mileage requirements, the battery pack structure is designed as $22PX95S$ consisting of 2090 cells and each cell is Sony VTC4-1850 Lithium-ion battery type (rate capacity is 2.1 Ah). Thus, the total capacity of the battery pack is 46.2Ah and the voltage is 399V. The model parameter settings in Equ. (1) and (2) are as follows: m - 1300 kg; A_f - 1.97 m^2; C_d - 0.33; μ - 0.018; η_1 - 0.9 and η_2 - 0.97.

2) Traffic dynamics: We collected three-month long (03/01/2016 – 05/31/2016) traffic data of the road segment [16] to train SAE model and one-week long traffic data in June for performance verification. Then, we estimated the queue length in the traffic light areas using our QL model and compared its estimation value with real data to verify its prediction accuracy.

3) Velocity optimization: To verify the performance of proposed velocity optimization method, at first we drove a vehicle twice on the chosen road section and recorded two driving velocity profiles (Fig. 7). One velocity profile is called as *mild driving profile* where the driver is expected to follow minimum velocity limit and accelerate gradually. The other driving velocity profile is called as *fast driving profile* where the driver drives fast without breaking traffic rules and accelerates quickly. Basically, the mild and fast driving profiles can represent smooth and harsh driving habits in real life. Then, we used these velocity profiles to compare energy and time consumptions. Here, we compared our velocity optimization method with a previous DP-based velocity optimization method [2], which do not consider queue lengthes in the traffic light areas. In the SUMO traffic simulator, we built the same road section map using OpenStreetMap and applied hourly available traffic data to create similar traffic dynamics [16].

B. Experimental Results

1) Energy consumption model: Simulation results of energy consumption model (Equ. (3)) under different velocities and accelerations are shown in Fig. 3. We can see that energy consumption of an EV increases faster when it accelerates. We can also find that energy consumption of pure EV is negative when it decelerates because of braking energy regeneration.

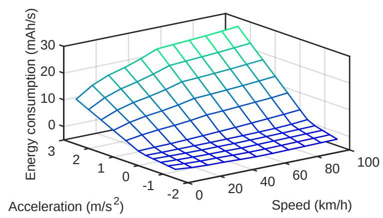
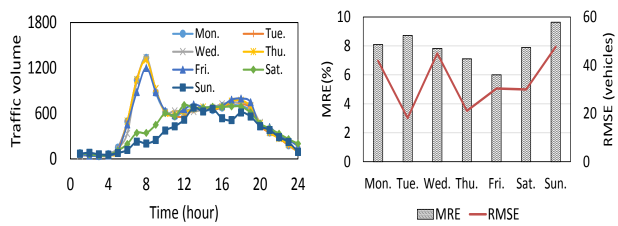


Fig. 3. Energy consumption of a pure EV (where θ = 0).

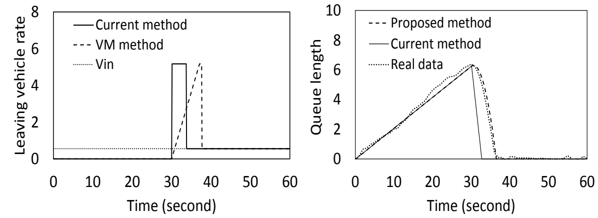
2) Traffic dynamics: To evaluate the trained SAE model, we used Mean Relative Error (MRE) and Root Mean Squared Error (RMSE). The real traffic volume in one week (from Monday, June 6^{st} to Sunday, June 12^{st}, 2016) is shown in Fig. 4(a) and MRE and RMSE of traffic volume predictions are presented in Fig. 4(b). All MRE values for seven days are less than 10% and RMSE values are relatively small compared with real traffic volume data, which confirms that traffic volume prediction based on SAE has relatively high estimation accuracy and can be used to predict vehicle arrival rate.



(a) Traffic volume in one week (b) Prediction performance

Fig. 4. Traffic volume prediction using SAE model.

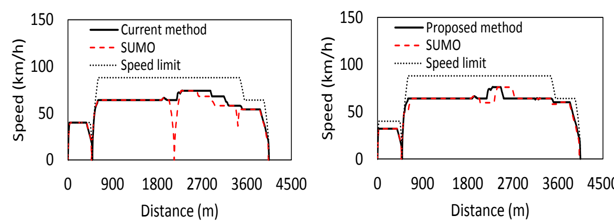
Next, to evaluate proposed VM model and QL model, we compared predicted vehicle leaving rate and queue length for a complete traffic signal cycle with real-life collected data. At 12:00 pm of June 2^{th}, 2016, we collected information of the second traffic light area of chosen road segment as follows: average inter-vehicle distance $\bar{d}$ is 8.5 m; ratio γ is 76.36%; vehicle arrival rate V_{in} is 1530 $vehicles/hour$; both red traffic signal duration t_{red} and green traffic signal duration t_{green} are 30 $seconds$. Fig. 5(a) shows vehicle leaving rate comparisons between proposed VM model and current methods in [9] that model $V_{out} = v_{min}/\bar{d}$. We can see that our VM model takes longer to reach $V_{out} = V_{in}$ since it considers acceleration in a waiting queue. Fig. 5(b) shows the comparison between the estimated queue lengths of different methods and the actual (collected) queue length. The current QL model [9] assumes the vehicle arrival rate is pre-known and that a vehicle can reach the minimum speed limit immediately when the traffic light turns green. We see that its predicted queue length is less accurately than our QL model. It is because our QL model considers the vehicle acceleration process when the traffic light turns green while the current QL model does not.



(a) Vehicle leaving rate (b) Queue length dynamics

Fig. 5. Traffic dynamics prediction of a traffic signal cycle.

3) Velocity optimization: We applied the optimal velocity profile of existing DP method in SUMO using TraCI interface and then SUMO produces slightly different velocity profile due to constraints such as collision avoidance and waiting in the queue in front of a traffic light. The comparison between the optimal velocity by existing DP method and the derived velocity profile from SUMO is shown in Fig. 6(a). We can see that derived velocity profile from SUMO experienced one stop at the first traffic light area and one large deceleration at the second traffic light area.

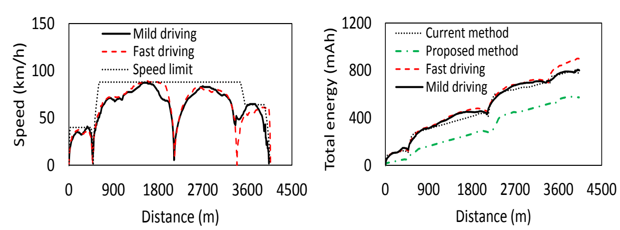


(a) Current method (b) Proposed method

Fig. 6. Evaluations of velocity optimization methods in SUMO.

The comparison between the optimal velocity profile of our proposed DP method and derived velocity profile from SUMO is shown in Fig. 6(b). Unlike Fig. 6(a), we can see that there is no stops or large decelerations at traffic light areas in Fig. 6(b) and the velocity in the road section from 0 m to 490 m is optimized to be lower so that the EV can pass by the first traffic light areas without meeting any waiting vehicles. Thus, we can conclude that our velocity optimization method outperforms existing velocity optimization methods since it enables EVs to immediately pass through traffic lights without meeting other waiting vehicles.

The total energy consumption comparisons for different velocity profiles are shown in Fig. 7(b). Here, we can see that velocity profile by proposed method generates less energy consumption compared with other velocity profiles. Specifically, the optimal velocity profile reduces total energy consumption by 17.5% and 8.4% compared with compared with fast driving

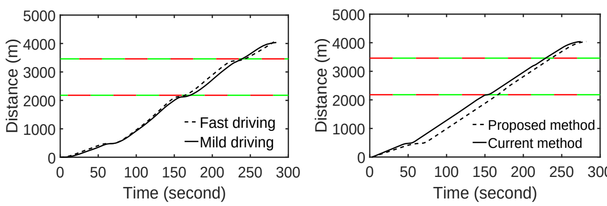


(a) Collected velocity profiles (b) Total energy consumption

Fig. 7. Energy consumption comparisons of different velocity profiles.

profile and mild driving profile, respectively. Besides, our proposed DP method requires 5.1% less energy than current DP method.

Finally, we conducted total driving time comparisons to check whether proposed method reduces energy consumption but sacrifices total driving time. Fig. 8 shows the required time of EV based on different profiles (with traffic light dynamics). The region with zero slope represents a location where the vehicle stopped. Our proposed method requires the same amount of time as fast driving pattern, which is 283 $seconds$, and requires less time than the current DP method. Therefore, we can conclude that our proposed velocity optimization method improves pure EV energy efficiency while reducing total driving time.



(a) Collected profiles (b) Optimized profiles

Fig. 8. Total driving time of different velocity profiles.

IV. Related Work

Several existing velocity optimization methods have been proposed to improve the fuel economy of vehicles. One group of works [1], [2] considers several traffic constraints such as stop signs, speed limit and driving pattern in velocity optimization to minimize total fuel consumption. Engin et al. [2] proposed a speed advisory system to determine the optimal speed trajectory along the route. It collects associated speed limit and stop sign information and chooses optimal velocity profiles using the DP algorithm. Christian et al. [1] designed an algorithm to determine optimal driving trajectories with predictive information about upcoming traffic events so that unnecessary acceleration/decelerations can be avoided. However, these works are more error-prone if there are multiple traffic lights during the trip. Another group of works [5], [17] considers multiple traffic lights and optimizes velocity profiles by allowing the vehicle pass through multiple traffic lights without any stops. However, these methods assume that the vehicle can immediately pass through traffic light areas, which is not practical if there are vehicles waiting in the traffic light areas. Our velocity optimization method considers the vehicles waiting in traffic signal areas to ensure that the vehicle passes through traffic signal areas without unnecessary stops or decelerations.

V. Conclusion

Major drawback of existing velocity optimization methods is the neglect of traffic dynamics in traffic signal areas. To overcome the drawback, in this paper, we propose a velocity optimization system for pure EVs with the consideration of the queue lengths in traffic signal areas. Basically, we build a QL model to predict the queue lengths in front of traffic lights and integrate this model in the DP algorithm so that EVs will not experience acceleration or deceleration due to meeting waiting queues in front of traffic lights. To improve estimation accuracy of QL model, we use the SAE model to predict vehicle arrival rate in real time and build a VM model to predict vehicle leaving rate. Our trace-driven simulation results from Matlab and SUMO show that our proposed velocity optimization method greatly reduces energy consumption compared with previous velocity optimization method while decreasing its trip time. In the future work, we will consider the effect of road gradient on the proposed system to check whether it will have great impact on optimization velocity profile.

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